UNIVERSITÀ DEGLI STUDI DI PADOVA

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Tesi di Laurea

# SENSOR DEPLOYMENT IN A BATTLEFIELD AND SENSOR ASSIGNMENT TO COMPETING MISSIONS.

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*Alla mia famiglia e ai miei amici.*

*The Sensor Utility Maximization model assumes that the budget is the demand and that the cost is the utility. Therefore, a solution cannot give a mission more than its demand. It is a reasonable model where there is a strong correlation between the utility (and therefore profit) to the cost.*

**Prof. Amotz Bar-Noy, City University of New York.**

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# Abstract

Questa tesi si colloca nell'ambito della International Technology Alliance (ITA), progetto che nasce dalla collaborazione tra l'ente di difesa statunitense e inglese. Tale progetto affronta problematiche relative alle operazioni militari svolte da coalizioni multinazionali e basate su una complessa rete di informazioni, in particolare qui si analizzano reti di sensori.

Quando non è presente una rete di sensori nel campo di battaglia, lo scopo è quello di dispiegare i sensori in maniera ottima nel campo in modo da soddisfare i requisiti di informazione di ciascuna missione. L'algoritmo per il posizionamento ottimo dei sensori è basato sul modello di programmazione lineare intera chiamato "Multiple Knapsack Problem". Tale algoritmo è stato implementato come un webservice ed è stato interfacciato con l'ambiente virtuale del gioco multi-player "Battlefield 2" per effettuare simulazioni realistiche.

Quando è disponibile una rete di sensori già dispiegata sul campo, è tipicamente richiesto il supporto di missioni simultanee in competizione per l'uso esclusivo dei sensori. Da ciò nasce la necessità di uno schema che assegni i sensori alle missioni. Qui consideriamo un approccio centralizzato, dove le decisioni vengono prese in un singolo nodo detto "base centrale". Tale schema è basato su un modello di programmazione lineare intera chiamato "Generalized Assignment Problem".

# Introduction

The aim of this thesis is to give a relevant contribution to the research on sensor networks, as part of the International Technology Alliance (ITA) project. This project is funded by the US Army Research Lab and by the UK Ministry of Defense, and it involves many US and UK universities, together with many big industries like IBM and Boeing. The aim of the ITA is to face the typical issues that arise during military operations carried on by multinational coalitions, in particular this thesis faces the problem of configuring sensor networks on which military operations have to rely.

The work done in this thesis can be subdivided into two big projects that are respectively described in Chapter 1 and Chapter 2. These two projects are very correlated even if it does not seem at a first look. In fact they are both aiming to configure sensor networks in such a way that the information requirements of one or more participants in a military operation are satisfied. Although these two projects were born as solutions to two different problems, they can be seen as one the extension of the other. In particular the solution that we developed for the problem faced in Chapter 1 constitutes the foundation on which we constructed the solution for the other problem described in Chapter 2.

The first project presented in Chapter 1 faces the problem of optimally deploying sensors in a battlefield, thus creating a sensor network that before didn't exists. The sensor network will be deployed with the goal to maximize the area covered by the sensors, while respecting the information requirements defined by the commander of a mission. In this project we only consider one participant at a time in each operation, i.e. each time that a sensor network

must be created there is only one commander who defines the information requirements from the battlefield. Anyway we also show that our solution can be easily adapted to deal with multiple missions.

We also describe how we modeled the problem as a Constraint Satisfaction Problem and in particular as an integer linear programming problem. Indeed, we extended an existing model, the *Multiple Knapsack Problem*, to include necessary informations about the properties of sensors and type of coverage needed in the battlefield. We present our implemented solution that is a combination of a Constraint Satisfaction Problem Solver and a brand new algorithm. Since the project aims also to simulate a real world scenario where we can actually deploy the sensors, the solution is implemented as a webservice to allow independence from the rest of the simulation environment. As environment to perform our tests we chose the virtual environment of the multi-player game "Battlefield 2", and we instrumented it to satisfy our needs. Finally we show the results of some experiment on the performances of our problem solver, and we analyze which are the most critical parameters.

The second project is presented in Chapter 2. The assumption here is that a sensor network is already deployed in a field, and in such a situation it is usually required to support multiple missions. Since missions might compete for the exclusive usage of the same sensing resources and since we want to deal with very large sensor networks, it becomes necessary to develop a sensor-mission matching scheme.

We formally define the Sensor Utility Maximization problem, an innovative approach to solve the sensor-mission matching problem. This problem can be formulated also as an integer linear programming problem, and it is here that we discover how the Sensor Utility Maximization model can be seen as an extension of the problem defined in Chapter 1. We decided to consider only centralized solutions in which the decisions on which sensors are selected and assigned to missions are made in a single node. We propose greedy algorithms and we implement a state-of-the-art preexistent algorithm improving its performances. Finally, we also show simulation results comparing the performances of these proposed solutions.

# Chapter 1

# Sensor Deployment in a Battlefield

## 1.1 Introduction and Motivations

This chapter describe the context of this project giving a brief overview of it, including also motivations and goals.

### 1.1.1 Context: the ITA project

This project is part of the ITA project which is an international project led by IBM[1] that addresses researches in the area of network-centric coalition operations. ITA stands for International Technology Alliance in Network and Information Sciences, and it involves many university in the USA and in the UK but the main participants are the defense departments of USA and UK since the results of these researches should be applied to military/rescue missions.

There are four main research areas defined by the alliance: (i) network theory, (ii) security across system of systems, (iii) sensor information processing and delivery, and finally (iv) distributed coalition planning and decision mak-

[1] website: www.ibm.com

ing. The department of Computing Science of the University of Aberdeen[2] is contributing mainly in (iii) and (iv), researching respectively:

1. Knowledge technologies for sensor information processing and delivery

2. Agent technologies for distributed coalition planning and decision making

This project is located inside the research field (1) that is in the area of sensor researches, in particular its aim is to help the commander of a mission to define needs of intelligence in certain zones of a map and then to provide the commander with the optimal deployment of the available sensors inside these zones. With regards to the ITA project, the most important aspect faced by this "Sensor Deployment" project is the scheduling of the capabilities of a sensor depending on which are the requirements given by the commander. So for example if there is need of VIDEO information in a certain zone, but the remaining sensors are all at the same time AUDIO/VIDEO sensors, then it will be possible to enable only the VIDEO ability of the sensor, in this way the autonomy of the sensor and also its performance can be increased. Indeed with only VIDEO enabled the sensor can decide to improve video quality, using the same energy spent with A/V enabled, or it could decide to maintain the same VIDEO quality, so that it will spend less energy and in this way the battery will last longer.

In this Chapter we will describe how we developed an automated reasoning technique that can generate a "strategic" deployment of sensors to cover the requirements of a mission. We will also show how we mathematically modeled the sensors and of the zones of a map, thing that in the future could be used as a base to create a sensor and a zone ontology.

### 1.1.2 Goal

Our project aims, as stated above, to develop an application to help the commander to define his needs of information in certain zones of a map and to give

[2]ITA project at Aberdeen: http://www.csd.abdn.ac.uk/research/ita/webpages/projects.html (last checked 06/05/2007)

in output an optimal deployment of the available sensors. Each sensor will be configured by enabling only certain sensor capabilities depending on the zone to which their are assigned to. So the problem, which is represented in Figure 1.1, can be informally defined in this way: Given a set of sensors each one with its own capabilities and a set of zones, each with its own type of information required, then the goal is to find an optimal deployment. With "optimal sensor deployment" we mean that the total area covered by the sensors has to be maximized, anyway we will see later that the concept "optimal" can be very flexible in our solution, since our theoretical approach to the problem is very flexible too.

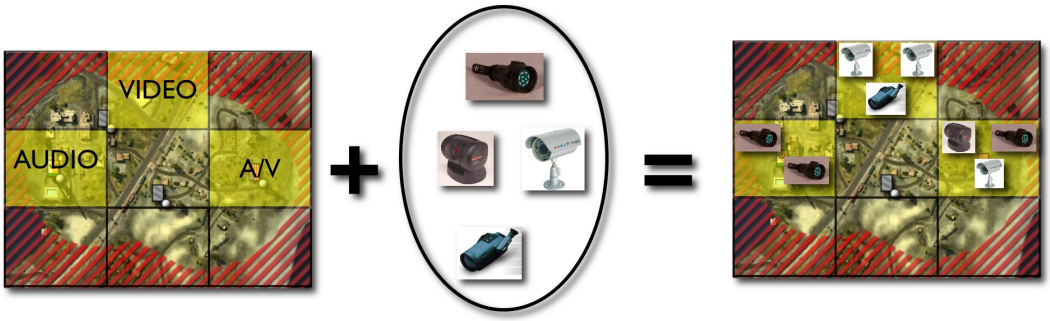



Figure 1.1: A graphic representation of the "Sensor Deployment" problem.

The project aims also to simulate a real world scenario, where we can simulate to deploy the sensors for real. We decided to use a virtual game environment where it is possible to actually deploy sensors and schedule their capabilities. Our choice is the virtual world of the PC game *"Battlefield 2"*, but our application, as we will see, will be completely independent from this particular game, so that in the future the virtual environment could be changed or could be substituted by the real world.

### 1.1.3 Motivations

The motivations of our project are pretty much the same that lie behind the ITA project, so overall there is the need to eliminate the pitfalls of compart-

mentalized research in different technical areas[3] and, through these researches, to provide unique capabilities to the US Army and the UK Armed Forces which could be used either in military or in rescue missions.

Note that in every military/rescue operation the first step is to place some intelligence in strategic zones (as it is stated in [2]), so that the soldiers know how they should prepare properly for the current mission. Since the first step is to deploy sensors and since the result of the mission depends strongly on the information gathered by the sensors, then it is compulsory to provide a sensor deployment as good as possible, such that it is able to maximize the possibilities of success of a mission.

Let's consider for example the case of a rescue mission in which some citizens got stuck in a flooded town. The commander will have to decide which are the zones relevant to the mission, let's say that these are the most densely populated areas of the town. Then the commander will decide which type of information should be required in each area, let's say AUDIO/VIDEO in some of them and in others only VIDEO. Our application will have to determine the optimal positions where to place the sensors and which capabilities of these sensors have to be enabled. Finally some soldiers could place the sensors, and the mission could start by using the information gathered by the sensors to decide which is the first zone to be rescued. So for example in a VIDEO zone the commander could see through the sensors that it is easier to reach this zone since it is not already completely flooded.

### 1.1.4 The virtual environment: "Battlefield 2"

As we said in advance, since we want to simulate a real world scenario, we used as a virtual environment the world of the PC game *"Battlefield 2"*, that you can see in Figure 1.2. The motivations behind this choice are mainly two: the tradition of the armed forces to use this kind of games to train soldiers,

[3]website: http://domino.research.ibm.com/projects/titans/www_titans.nsf/pages/proj.html, checked on 06/05/2007

and the architecture of the game.

Figure 1.2: Map of BF2 on the left, an example of playing on the right.

With regards to the first reason, the US Army uses shooting online games (obviously with a private server) to train soldiers, i.e. they put a bunch of soldiers in a situation where they have to accomplish a mission and the commander monitors them by observing the way in which they behave while playing. So this is not a ”body” or a ”reflex” training but it is a way to improve the strategy applied by each team of soldiers to accomplish a mission. In conclusion we decided to use *”Battlefield 2”* since there is an high probability that soldiers already played a similar game and so if the system developed during this project should result really interesting with regards to the ITA project, then it could be also easily tested by the army.

The second motivation that led us to choose *”Battlefield 2”* is its architecture. Indeed it is a shooting online game, that has the typical architecture of an online game: it has a server and a client. The players will play by starting the client of the game in their machine and then by connecting to the server that manages all the interactions with the environment and with other players. Furthermore it is ”open”, which means that it is easy to gather data and events from the game, so we can actually know what is happening inside the game. This can be done by writing some code in Python that we can easily add to

the game server. In fact this is another important reason that led us to the choice of using *"Battlefield 2"*: it is easy to create "plug-in's" for the server writing our own Python code. Such a "plug-in" is called "Mod" (that stands for "modified" game) and since there were already many "Mod" available on the Internet, like*Project Reality*[4], it was evident that it should have been quite easy to develop a "Mod" for this game.

## 1.2 Related Work

In this Section we give a brief description of the most relevant works produced on the sensor deployment research area, even if as you will see only one paper is really interesting for us. We will also introduce a project, developed in the Computing Science Department of the University of Aberdeen, which is closely related to this "Sensor Deployment" project.

### 1.2.1 Previous works on sensors

The most relevant work for this project is a paper published by IEEE entitled *"Decision-Theoretic Cooperative Sensor Planning"*[6]. This paper describes a decision-theoretic approach to cooperative sensor planning between autonomous vehicles executing a military mission. Simple stated: given a set of Unmanned Ground Vehicles (UGV) each with sensors installed, they use intelligent cooperative reasoning to select optimal vehicle viewing locations and to select optimal camera pan and tilt angles throughout the mission. This is a problem of optimization too, like our "Sensor Deployment" problem, indeed the decisions are made in such a way to maximize the value of information gained by the sensors while maintaining vehicle stealth.

As it can be noticed there are many things in common with our project but also many different aspects. Anyway the fact that in [6] sensors are mobile

[4]which was actually a complete revised version of *"Battlefield 2"* (like a new different game) showing the infinite possibilities of editing this game. Website: http://www.realitymod.com/

could bring someone to think that this is a big difference with our project, instead also our approach can be extended to the case where the sensors are mobile, as we will see in Section 1.3.

The most important thing in common with our project is that they try to compute an optimal location, camera pan and split that can maximize the covered area for each vehicle, i.e. they are trying to solve a problem that is very similar to our problem. The difference is that they do not have a commander who specifies which zones have to be covered and which type of information is required. Instead their commander will only define the value of information gathered, for example a commander could decide that the value of information gathered about the kind of enemy forces that is in the area (tank, trucks, etc,) is the highest valued information, and so the UGV's will try to find a location from where they can maximize this type of information.

At the beginning of our project we also thought to use a similar way of giving a value to the information and then to deploy sensors maximizing this value. Anyway such a solution turned out to be too complex and it also involved some aspects that were irrelevant to this project.

Other papers on sensors are available, like in [13] or [9], but none of them face a problem similar to the optimal sensor deployment. Anyway it is to note that [9] can be considered very relevant to the branch of the ITA project that involves sensor networks (which is more or less the same branch to which this project belongs to).

### 1.2.2 The project “Plan and Play”

The "Plan and Play" [11] is the single honours project of Daniele Masato who developed this project at the Computing Science Department of the University of Aberdeen. "Plan and Play" is closely related to this project, since our project uses some concept and technologies developed in Masato's project.

Plan and Play finds its collocation in the domain of e-Response, a group of network technologies designed to support emergency response operations as humanitarian relief and civilian population control. The project focuses on human and software agent interactions in a virtual environment where the collaboration between them is required in order to carry out a plan. So this project aims to track the progresses achieved in a plan by each player by mapping the plan and its various steps to states and objects within the virtual universe.

The links between "Plan and Play" and our project are the architecture of the system and the virtual environment used. Indeed the architecture of Masato's project is based on a central component that is represented by a webservice written in Java which implements a planner, and as you will see in Section 1.3.1 also the "Sensor Deployment" project is based on such a webservice.

Another important link between these two projects is the use of the same virtual environment that is *"Battlefield 2"*. In the project "Plan and Play", Masato implemented another webservice (written in Python) inside the game server[5] that exchanges messages with the webservice written in Java but the "Sensor Deployment" project didn't need such a complicated "Mod"[6] of the game, so as we will see in the Section 1.3.1 we only took the same structure of the "Mod" (that is a standard for every Mod) and we deleted the webservice in Python inside the "Mod" keeping only some useful methods to interact with the remaining part of the system.

[5]The other webservice is the one that implements the planner that is actually completely independent from the game and also situated outside of it.

[6]See Section 1.1.4

### 1.2.3 Constraint Satisfaction Problem and Constraint Programming

This section describes what is a Constraint Satisfaction Problem (CSP) and what is Constraint Programming (CP) which are two concepts that we widely used throughout all this project. We also describe three different Constraint Satisfaction Problem that are really important with respect to the theoretical part described in this document.

#### Definitions: CSP and CP

The "sensor assignment" problem that we stated above in 1.1.2 can be seen as a *Constraint Satisfaction Problem (CSP)* that is a mathematical problem where one must find values for variables that satisfy a number of constraints. CSPs are the subject of intense research in both artificial intelligence and operational research. Many CSPs require a combination of heuristics and combinatorial search methods to be solved in a reasonable time.

The techniques used to solve a CSP depend on the kind of constraints being considered. Constraints on a finite domain are often used, to the point that constraint satisfaction problems are typically identified with problems based on constraints on a finite domain. Such problems are usually solved via search, in particular with a form of backtracking or local search. Constraint propagation are other methods used on such problems; most of them are incomplete in general, that is, they may solve the problem or prove it unsatisfiable, but there could be cases in which this is not possible. Constraint propagation methods are also used in conjunction with search methods to make a given problem simpler to solve.

*Constraint programming* is the programming paradigm where relations between variables can be stated in the form of constraints. Constraints differ from the common primitives of other programming languages in that they do not specify a step or sequence of steps to execute but rather the properties of a solution to be found.

The constraints used in constraint programming are of various kinds: those used in constraint satisfaction problems, those solved by the simplex algorithm, and others. Constraints are usually embedded within a programming language or provided via separate software libraries. In our case we will use a Java software library called "CHOCO"[7] that allows us to specify constraints that will be used by CHOCO itself to solve the "Sensor Deployment" problem with its own methods used to solve CSP problems.

### The eight queens problem

From what stated above, we can easily understand that to solve a CSP it is enough to specify its constraints with a programming language using some separate software libraries. So it is clear that the tricky part is not to solve the problem but to create a mathematical model for the problem, that is to define variables, the domain of the variables and the constraints for the problem.
We can understand this by analyzing a CSP problem called "the eight queens problem", which is quite related to the "Sensor Deployment" problem since it is a placement problem too. In the eight queens problem we have to place eight chess queens on a 8×8 chessboard in such a way that each queen does not attack another queen using the standard chess queen's moves. This problem, as many CSPs, has more than one solution, and you can see one of this possible solution in Figure 1.3. So it is clear that a solution requires that no two queens share the same row, column, or diagonal. The eight queens puzzle is an example of the more general "n queens problem" of placing n queens on an $n \times n$ chessboard.

So now that we informally defined the *"n-queens problem"*, we can try to find a mathematical model for this problem. The components of a model are always three:

1. *Variables* whose final values have to respect the constraints.

2. *Domain* of the values that variables can assume.

[7] For more information see Section 1.4.

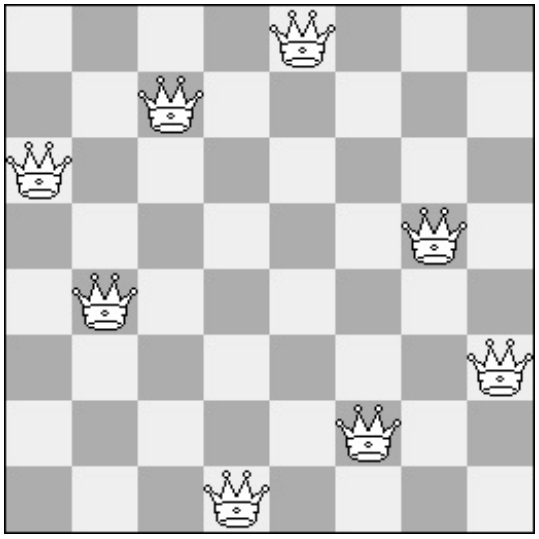


Figure 1.3: A possible solution to the 8 queens problem.

3. *Constraints* on the variables.

And in the case of the *"n-queens problem"* as presented in the book [1]:

**Variables :** $x_1, \ldots, x_n$. where $x_i$ denotes the position of the queen placed in the $i$th column of the chess board.

**Domain for each variable :** the integer values $[1, \ldots, n]$ .

- So for example, the solution presented in Figure 1.3 corresponds to the sequence of values (6,4,7,1,8,2,5,3), since the first queen from the left is placed in the 6th row counting from the bottom, and similarly with the other queens.

**Constraints :** They can be formulated as the following disequalities for $i \in [1 \ldots n-1]$ and $j \in [i+1 \ldots n]$

- No two queens in the same row:

$$x_i \neq x_j \tag{1.1}$$

- No two queens in each South-West – North-East diagonal:

$$x_i - x_j \neq i - j \tag{1.2}$$

- No two queens in each North-West – South-East diagonal:

$$x_i - x_j \neq j - i \tag{1.3}$$

There is a big difference between an informal description of the problem and the mathematical model which represents it, indeed we have to reach a very high level of abstraction.

### The Knapsack Problem

The knapsack problem is a CSP that derives its name from the maximization problem of choosing some items that can fit into one bag (of maximum weight) to be carried on a trip, you can see its graphic representation in Figure 1.4. An informal description[8] of it could be that we are given a set of items, each with a cost and a value, and a knapsack with a given cost, then we have to determine which items to insert in the knapsack so that:

- the *total cost* of the chosen items is less than or equal to the knapsack's cost,

- the *total value* of the chosen items is as large as possible.

In this case it is easier to derive a formal model than in the case of the eight queens problem, in fact it comes straight forward that the features of the model are:

**Variables :** $x_1, \ldots, x_n$ , where:

[8]Here we are actually considering a particular type of knapsack problem called 0-1 knapsack problem, since the items can be chosen ($x_i = 1$) or not chosen ($x_i = 0$). Instead a more general knapsack problem can also decide to take more than only one instance of the same object to insert inside the knapsack.

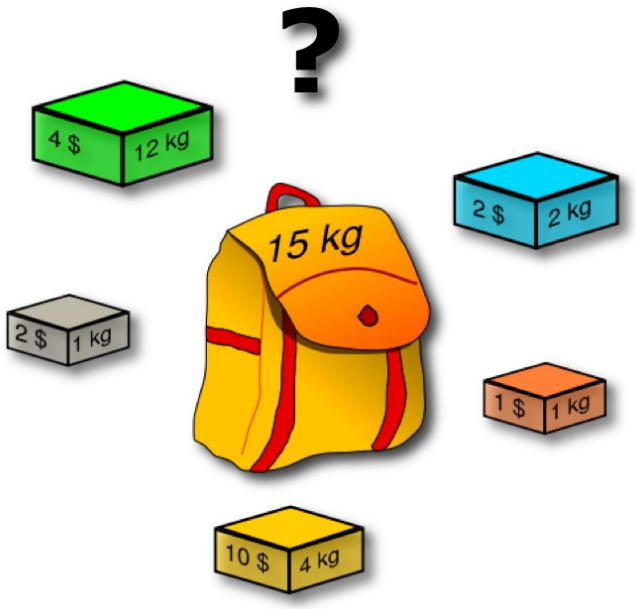



Figure 1.4: The knapsack problem.

$$x_i = \begin{cases} 1 & \text{if item } i \text{ is inserted in the knapsack} \\ 0 & \text{otherwise} \end{cases}$$

For each item $i$ we define also two constants:

$$w_i := \text{the cost (or weight) of the item } i$$

$$p_i := \text{ the value (or profit) of the item } i$$

And one more constant for the knapsack:

$$c := \text{ knapsack's capacity (or cost)}$$

In the following description of the model we will assume that:

$$w_i \leq c \tag{1.4}$$

so that each item can be (individually) inserted inside the knapsack, and also that:

$$\sum_{i=1}^{n} w_i \geq c \tag{1.5}$$

otherwise all the items could be inserted inside the knapsack and this would be the optimal solution.

**Domain:** the integer values [0,1] .

**Constraints :**

$$\sum_{i=1}^{n} w_i \cdot x_i \leq c \tag{1.6}$$

$$\max \sum_{i=1}^{n} p_i \cdot x_i \tag{1.7}$$

The first constraint says that the total cost of the chosen items has to be less than or equal to the knapsack's cost, and instead the second constraint states that the *total value* of the chosen items has to be as large as possible.

The last constraint that maximizes a function is also usually called *"Objective Function"* and it allows to find the optimal solution between the many possible solutions to the problem.

The solution of the problem will be a set of values each assigned to a variable: each variable $x_i$ will have a value 0 or 1, where if $x_i = 1$ the item $i$ had been chosen to be inserted inside the knapsack. This solution will be also optimal, since the constraint 1.9 states that the total value has to be the highest.

It is to note that a problem similar to the *"knapsack problem"* often appears in business, cryptography and applied mathematics[9].

### The Multiple Knapsack Problem

The *Multiple Knapsack Problem*[10] an NP-complete[11] Constraint Satisfaction Problem, i.e. a very hard to solve problem. It is substantially a generalization of the *Knapsack problem* explained in the previous Section 1.2.3, indeed the problem is the same except for the fact that instead of a single knapsack there are many knapsacks, each with a different cost, where to insert the items. You can see a graphic representation of the problem in Figure 1.5.

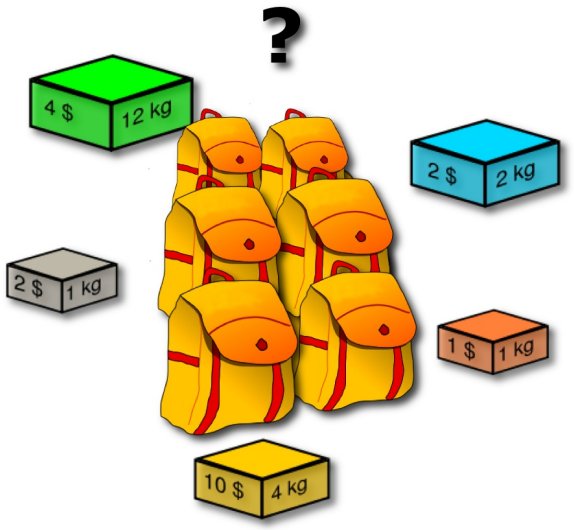



Figure 1.5: Multiple Knapsack Problem

[9]See http://en.wikipedia.org/wiki/Knapsack_problem , last checked on 09/05/07

[10]Also in this case we are actually considering a particular type of multiple knapsack problem called 0-1 multiple knapsack problem, since the items can be chosen ($x_{i,j} = 1$) or not chosen ($x_{i,j} = 0$) . Instead in the more general knapsack problem we can also decide to take more than only one instance of the same item $i$ to insert inside the $j$th knapsack, so for example $x_{i,j} = 3$ means that we are taking three instances of the item $i$ and inserting them inside the $j$th knapsack.

[11]Also the single knapsack problem is NP-Complete.

Let's analyze the formal CSP model in this case:

**Variables:**

$$x_{i,j} = \begin{cases} 1 & \text{if item } i \text{ is in knapsack } j \\ 0 & \text{otherwise} \end{cases}$$

$$\forall i \in \mathbf{N} = \{e_1, ..., e_n\} \qquad \text{Set of items}$$

$$\forall j \in \mathbf{M} = \{K_1, ..., K_m\} \qquad \text{Set of knapsacks}$$

For each item $i$ we define two constants:

$$w_i := \text{the cost (or weight) of the item } i$$

$$p_i := \text{ the value (or profit) of the item } i$$

And we also define a constant for each knapsack:

$$c_j := \text{ capacity (or cost) of knapsack } j$$

In the following description of the model we will assume that:

$$\max_{i \in N}\{w_i\} \leq \max_{j \in M}\{c_j\} \tag{1.8}$$

that means that each item can be inserted in at least one knapsack, and we assume also that:

$$\min_{j \in M}\{c_j\} \geq \min_{i \in N}\{w_i\} \tag{1.9}$$

which means that each knapsack can contain at least one item.

**Domain:** the integer values [0,1] .

**Constraints:**

- To ensures that the total cost of items inserted in the $j$th knapsack is less than the cost of the $j$th knapsack:

$$\sum_{i \in N} w_i \cdot x_{i,j} \leq c_j \qquad \forall j \in M \tag{1.10}$$

- To ensures that each item will be inserted in no more than one knapsack:

$$\sum_{j \in M} x_{i,j} \leq 1 \qquad \forall i \in N \tag{1.11}$$

- And finally we have the *"Objective Function"* that states that we have to maximize the total value of items inserted in each knapsack:

$$\max \sum_{i \in N} \sum_{j \in M} p_i \cdot x_{i,j} \tag{1.12}$$

Note that we could also adapt the *"Objective Function"* to our needs, by changing it. Furthermore as we will see in Section 1.3.3, this model will be the basis over which we will develop the model for our "Sensor Deployment" problem. Indeed we will take this model and we will expand it with additional constants and other constraints.

## 1.3 Concept and Design

This is the most important Section since it describes the solution developed to solve our problem, but it also gives an overview of the system and an idea of the first attempt that we did to solve the problem. In particular it is very interesting how we managed to learn from our mistakes, and how this brought us to a very good and innovative solution.

### 1.3.1 System Architecture

The architecture of the system is an architecture composed by three components, as you can see in figure 1.6.

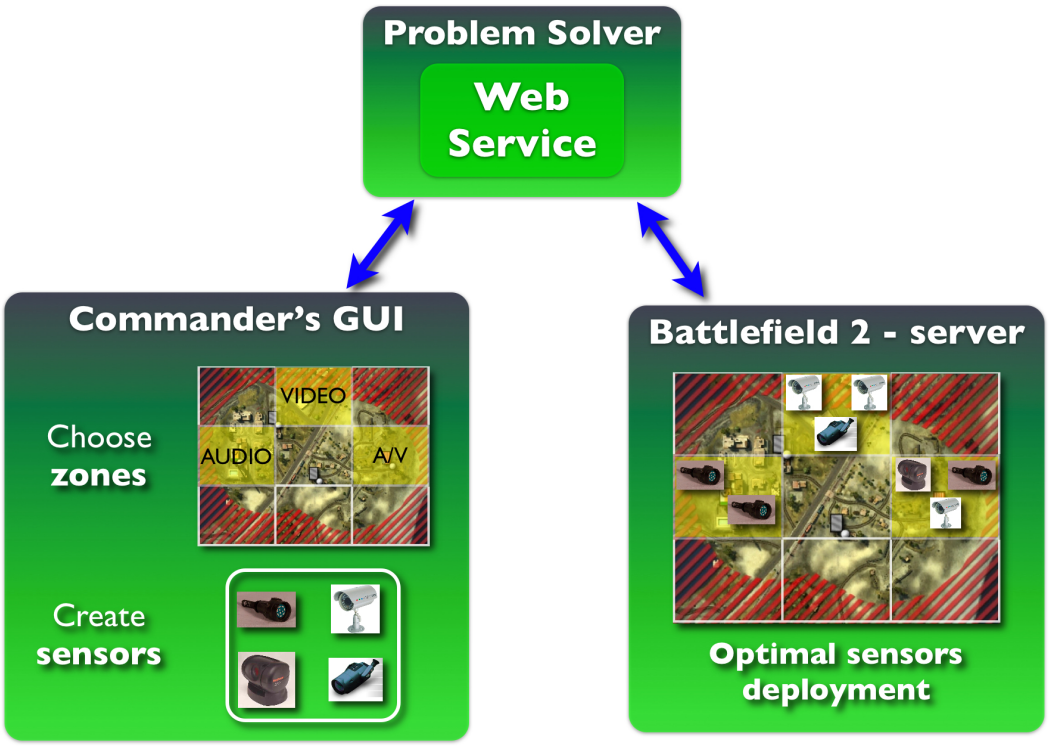



Figure 1.6: System Architecture

The most important component is the solver, which is an application that solves the problem of finding an optimal deployment of the sensors inside the zones of a map given by the commander of a mission. This is implemented as a webservice and it represents actually the core of the system, since the remaining two components will interact each other using this webservice as computation and communication node. It is to note that to implement the solver we chose the webservice paradigm since in this way the other two components can be easily substituted with different applications if needed. So for example we could replace the commander's interface with a more user-friendly one and the game *"Battlefield 2"* with another virtual environment or also

with the real world.

The second component is the commander's interface, which allows the commander to choose the zones from a map and to define which type of information it is required from each of them. At the same time it allows the commander to insert data about the available sensors, i.e. the number of sensors together with a set of properties for each one of them. The Commander's Interface will send to the solver the information about the sensors and about the zones selected, so later the solver will solve the problem. It is to note that the solution of the problem remains inside the solver as a static variable, so that at any time the webservice will contain the current optimal sensor deployment (if there exists one).

The last component is the *mod*[12] developed for *Battlefield 2* that actually modifies the behavior of the game server so that when some players connect to it to play a match, this will ask for the current optimal sensor deployment stored in the webservice, and then it will create the sensors inside the map. Anyway we will see in Section 1.4 that the game is quite limited since the only way in which we can simulate sensors inside the game is creating a sensitive invisible area that will let us know only what enters and what exits from it.

### 1.3.2 Modeling the Sensor Deployment as a CSP

Here we describe the real challenge that we faced, that is to create a model for the *"Sensor Deployment"* problem. The model for this problem will be implemented later as a webservice and it will actually constitute the core of the system.

In this Section we present the first model that we created for the problem, and as we will notice later we will see that this first model is not appropriate for this problem. Anyway this model is described in the same way that we will use to present the final model since we want to describe each step that led us to develop it.

[12]See Section 1.1.4

The first model that we developed is inspired by the eight queens problem, in particular it idealizes the map as a big chessboard where each possible position in the map corresponds to a cell in the chessboard. Furthermore between the constraints that we will use, we can find one that is very similar to one of the constraint of the eight queens problem.

In this first model we first developed a simplified representation for sensors and zones, that actually could represent an ontology for sensor and zone, indeed this idealization will be reused in the correct model. So in particular we have:

**Sensor:** it is idealized as a circular area having: a radius ($r_i$), a center ($x_i, y_i$), the type of information that the sensor can gather (e.g. AUDIO). You can see in Figure 1.7 the graphic representation of a sensor.

**Zone:** it is represented by: a set of four coordinates that determines the boundaries of a rectangular zone, and the type of information needed (e.g. AUDIO required). In Figure 1.7 we show the graphic idealization of the zone.

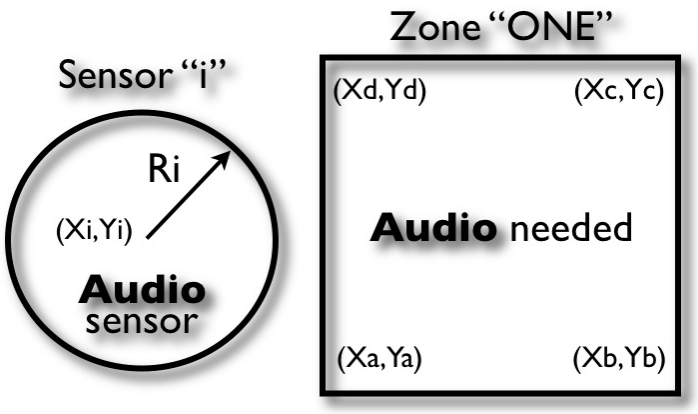



Figure 1.7: Representation of a sensor and a zone in the first model.

Now we can define the formal mathematical model that uses the idealization showed above:

**Variables:** $\{(x_1, y_1), \ldots, (x_n, y_n)\}$
that is a list of $(x_i, y_i)$ coordinates of the center of each sensor.

**Domain:** each (x,y) inside the boundary of the map

**Constraints:** The constraints can be divided into two types:

1. *System Constraints* that are actually the constraints proper of the sensor network, so:
   - All the sensors have to be assigned to a different position in the map:

     $$(x_i, y_i) \neq (x_j, y_j) \qquad \forall i, j \in \{1, \ldots, n\}, i \neq j \tag{1.13}$$

     Note that this constraint is really similar to the constraint (1.1) used in the eight queens model in Section 1.1.
   - The area of a sensor must not intersect the area covered by another sensor, and we implemented this constraint by using the fact that two circles intersects when the distance between their centers is less than the sum of their radii:

     $$distance((x_i, y_i), (x_j, y_j)) \geq |r_i + r_j| \qquad \forall i, j \in \{1, \ldots, n\}, i \neq j \tag{1.14}$$

2. *Commander's Selection Constraints* that are the constraints imposed by the commander when he selects zones in a map and he decides which type of information it is needed from these zones:
   - First of all we divide the sensors in classes considering the type of information gathered by sensors, so we will have three different classes[13]:

     **AUDIO sensors** assume that they are $i \in \{1, \ldots, l\}$

     **VIDEO sensors** assume that they are $i \in \{l + 1, \ldots, m\}$

     **A/V sensors** assume that they are $i \in \{m + 1, \ldots, n\}$

[13] Here we consider only three type of information: AUDIO, VIDEO and AUDIO/VIDEO. Anyway this will be extended in the next Sections.

- Now the following constraint states that there must be only AUDIO sensors in the AUDIO zones selected by the commander. So *for each AUDIO zone* we have:

$$x_a \leq x_i \leq x_b \qquad \forall i \in \{1, \ldots, l\}, \tag{1.15}$$

$$y_a \leq y_i \leq y_d \qquad \forall i \in \{1, \ldots, l\}, \tag{1.16}$$

  where each AUDIO zone has coordinates $\{(x_a, y_a), (x_b, y_b), (x_c, y_c), (x_d, y_d)\}$ like in Figure 1.7.

- In the same way, *for each VIDEO zone* we have:

$$x_a \leq x_i \leq x_b \qquad \forall i \in \{l, \ldots, m\}, \tag{1.17}$$

$$y_a \leq y_i \leq y_d \qquad \forall i \in \{l, \ldots, m\}, \tag{1.18}$$

- And finally, *for each A/V zone* we have:

$$x_a \leq x_i \leq x_b \qquad \forall i \in \{m, \ldots, n\}, \tag{1.19}$$

$$y_a \leq y_i \leq y_d \qquad \forall i \in \{m, \ldots, n\}, \tag{1.20}$$

Note that the information about the capabilities of each sensor must be stored outside the mathematical model, in some data structure. Viceversa, we can see that the data about the type of information required from each zone is included in the model thanks to the subdivision of the zones into classes. In the last model that we will present in Section 1.3.3, we will see how we managed to include inside the model also the information about the capabilities of each sensor without using an external data structure.

We didn't used any *"Objective Function"* and this is why we wanted to test how the model was working without having to find an optimal solution, but only having to find a solution even not optimal. After an implementation step and some tests we found out that the solver which was using this model was of a very poor quality, since in many cases it was even not able to find a (non

optimal) solution in a reasonable time.
Furthermore we also realized that we were not considering the problem of scheduling of the capabilities of a multimodal sensor[14]. So for example we were assigning only VIDEO sensors to a VIDEO zone and we were not allowing the case in which an A/V sensor could be assigned to a VIDEO zone having only the VIDEO capability enabled.

To finish this description of the model we would like to analyze the reasons why this model did not have good performances. The main reason is that the domain of this model was too big, in fact taking a closer look at the domain of the CSPs described in the previous Section 1.2, we can notice that those domains are really small, sometimes composed by only two elements (e.g. {0,1}). So it is comprehensible that our model did not work well since our domain includes each possible position inside a map, that if we have a square map with a side of 512 meters, the domain will have $512 \times 512 = 262144$ elements. Here we are considering that the unit of the map is one meter, and so the smallest distance between two sensors will be one meter. At the beginning we thought to reduce the domain by taking a unit bigger than one meter inside the map. So for example by taking 8 meters as a unit in the map we would have reduced the domain of a factor $8^2$, indeed the number of positions allowed in the map now becomes $64 \times 64 = 4096$. Although in this way the domain became smaller than before, it was still too big compared to the domains which ares used in the classic CSPs, and in addition since we used a bigger unit for the map we lost precision (now the smallest allowed distance between two sensors is 8 meters). Finally we decided that this was not the right model and we began to work on a new model.

### 1.3.3 Reformulation using the multiple knapsack problem

In this section we will describe the final version of the model developed for the "Sensor Assignment" problem. This model is actually the most important

[14] i.e. a sensor with many capabilities (or type of information gathered).

part of this project and as a matter of fact its development took the most part of the time spent to complete this project.

The intuition behind this model is to think at the *"Sensor Deployment"* problem as a *"Multiple Knapsack Problem"* described in Section 1.2.3, and to use a similar model for it. This new conception of the problem lead us to divide the main problem described in Section 1.1.2 into two separate subproblems:

- The *"Sensor Assignment"* problem that is to assign sensors to zones considering only the zones selected by the commander and the type of info required from them.

- The *"Sensor Deployment"* problem that is for each zone to deploy only sensors assigned to that particular zone.

This subdivision is very important since it allows also to introduce the scheduling of the capabilities of a multimodal sensor. In fact, just after having found a solution to the "Sensor Assignment" problem, for a certain sensor with more than one capability we can choose which capabilities have to be enabled depending on the assigned zone. So for example if an A/V sensor is assigned to an AUDIO zone, then we will enable only the AUDIO resource of that A/V sensor.

In the following paragraphs we will describe more in detail the two different subproblems that will be solved in sequence one after the other and will give us the optimal sensor deployment.

### Sensor Assignment

As we stated above, this problem aims to assign sensors considering only the zones selected by the commander and the type of information that he needs from these zones, this problem takes also into account the fact that sensors with many capabilities can be assigned to a zone that does not require that all the sensor capabilities have to be enabled.

So a formal description of the problem, represented in Figure 1.8, could be: given a set of zones selected by the commander each with its own type of information required, and a set of sensors each with its own capabilities, then we will have to assign each sensor to a zone maximizing the total area covered by sensors. Note that at the end of this problem we will not have as a result the exact positions in which we have to deploy sensors, but we will get only the zone where each sensor has to be deployed.

Thanks to this new point of view on the problem definition we are actually reducing the domain with respect to the one of the model presented in the Section 1.3.2. Indeed we are no more considering every possible position inside the map, instead we are now taking into account only the zones selected by the commander and not even including the positions that are not allowed in the definition of the problem . In Figure 1.8 we put some red crosses on the zones that are not selected by the commander to represent the domain reduction.

Figure 1.8: Representation of the Sensor Assignment Problem in the final model.

As we said above the model developed for this subproblem called “Sensor Assignment”, is substantially the model of the multiple knapsack extended with other constraints and other constants to include inside the model the information about the capabilities of the sensors and about the type of information required from each zone. To begin with let’s try to point out which are the *analogies*, represented in Figure 1.9, between the multiple knapsack problem

and the "Sensor Assignment" subproblem:

- Knapsacks $\Longleftrightarrow$ Zones selected,
- Knapsack's cost $\Longleftrightarrow$ Area of a selected zone,
- Items $\Longleftrightarrow$ Sensors,
- Item's cost $\Longleftrightarrow$ Area covered by the sensor,
- item's value $\Longleftrightarrow$ Area covered by the sensor

In particular we note the last two analogies stating that in this case we are using a specific case of the multiple knapsack problem where $p_i = w_i$ for each sensor (or item), so since now we will use only the symbol $w_i$ to indicate either the item's cost or the item's value.

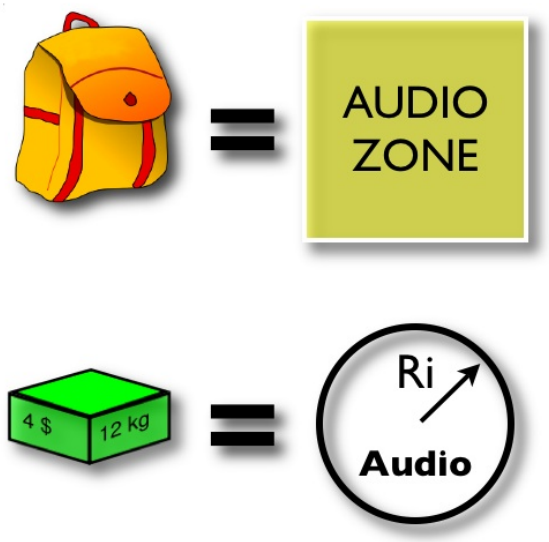



Figure 1.9: Analogies between the multiple knapsack and the Sensor Assignment problem.

Here we present the mathematical model for the problem:

**Variables:** We use a two-dimensional variable, to resolve the problem:

$$x_{i,j} = \begin{cases} 1 & \text{if sensor } i \text{ is in zone } j \\ 0 & \text{otherwise} \end{cases}$$

$$\forall i \in \mathbf{N} = \{s_1, ..., s_n\} \qquad \text{Set of sensors}$$

$$\forall j \in \mathbf{M} = \{Z_1, ..., Z_m\} \qquad \text{Set of zones}$$

And then we use some constant terms for each sensor and for each zone:

$$t_{a_i} = \begin{cases} 1 & \text{if sensor } i \text{ has AUDIO} \\ 0 & \text{otherwise} \end{cases}$$

$$t_{b_i} = \begin{cases} 1 & \text{if sensor } i \text{ has VIDEO} \\ 0 & \text{otherwise} \end{cases}$$

$$w_i = \text{area covered by sensor } i$$

$$c_j = \text{area of the zone } j$$

Note that an AUDIO/VIDEO sensor will have $t_{a_i} = 1$ and $t_{b_i} = 1$.
Below, we also subdivide the set of zones into subsets, each subset is composed by zones from which the commander requires the same type of information:

$\mathbf{M_a} = \{Z_1, ..., Z_l\}$, Set of zones from which AUDIO is required.

$\mathbf{M_b} = \{Z_{l+1}, ..., Z_f\}$, Set of zones from which VIDEO is required.

$\mathbf{M_{a,b}} = \{Z_{f+1}, ..., Z_m\}$, Set of zones where both AUDIO and VIDEO are required.

**Domain:** the integer values [0,1] .

**Constraints:**

- The following constraints are the proper constraints of the multiple knapsack problem, like the constraints described in the Section 1.2.3:

$$\sum_{i \in N} w_i \cdot x_{i,j} \leq c_j \qquad \forall j \in M \tag{1.21}$$

$$\sum_{j \in M} x_{i,j} \leq 1 \qquad \forall i \in N \tag{1.22}$$

- The constraints below were added to respect the commander's choices, in terms of type of information needed in each zone. This is one of the most important part of the model since it extends the basic model of the multiple knapsack into a more complex one:

  The following constraint is to have only sensors with AUDIO enabled in AUDIO zones:

$$\sum_{i \in N} t_{a_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_a \tag{1.23}$$

  The following constraint is to have only sensors with VIDEO enabled in VIDEO zones:

$$\sum_{i \in N} t_{b_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_b \tag{1.24}$$

The following constraint is to have only sensors with A/V enabled in A/V zones:

$$\sum_{i \in N} t_{a_i} \cdot t_{b_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_{a,b} \tag{1.25}$$

- And, as the last part of the extension of the multiple knapsack model, we add the following constraint to ensure that there is at least one sensor in each zone:

$$\sum_{i \in N} x_{i,j} \geq 1 \qquad \forall j \in M \tag{1.26}$$

**Objective function:** In this case we preferred to treat the objective function in a separate paragraph, even if it can always be considered a constraint. We developed two different objective functions and we decided to use the second one.

- The first possibility for the objective function maximizes the total area covered by the sensors, considering the zones altogether:

$$\max \sum_{i \in N} \sum_{j \in M} w_i \cdot x_{i,j} \tag{1.27}$$

- Now the second possibility for the objective function, that is the function that we chose in the implementation, minimizes the number of sensors used and at the same time maximizes the total area

covered by the sensors:

$$\max \sum_{i \in N} \sum_{j \in M} w_i \cdot x_{i,j} - \sum_{j \in M} \sum_{i \in N} x_{i,j} \tag{1.28}$$

In the future we could also change this objective function into a more complex one.

Note again that in the context of this subproblem the coordinates of the boundaries of each zone do not matter, we will pay attention to them only in the next subproblem called "Sensor Deployment".

Furthermore, it is now possible to configure the resources of each multimodal sensor by switching on or off some of these different capabilities. For example if an AUDIO/VIDEO sensor is assigned to an AUDIO zone, then we will enable only the AUDIO capability with the purpose of saving battery power. Battery life is indeed one of the hardest issues to solve when we have to configure sensor networks, and with this in mind we can state that this model is quite an important contribution to the researches in sensors networks.

Finally, we would like to point out that this model is an innovative model since there is no evidence of other researches that applied an extension of the multiple knapsack model to the field of sensor assignment. This led us also to write a research paper [12] on this work that will be published in the Proceedings of the Twenty-seventh SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence.

### Sensor Deployment

This problem has to be solved separately for each zone, and it can be solved only after having found a solution for the subproblem called "Sensor Assignment". A formal description for this second subproblem, represented in Figure 1.10, could be: given a zone and given the subset of sensor assigned to this zone, then we will have to deploy each sensor inside the zone with the constraint that the areas covered by any two sensors do not overlap.

First of all we have to point out that this is not properly a CSP, but it

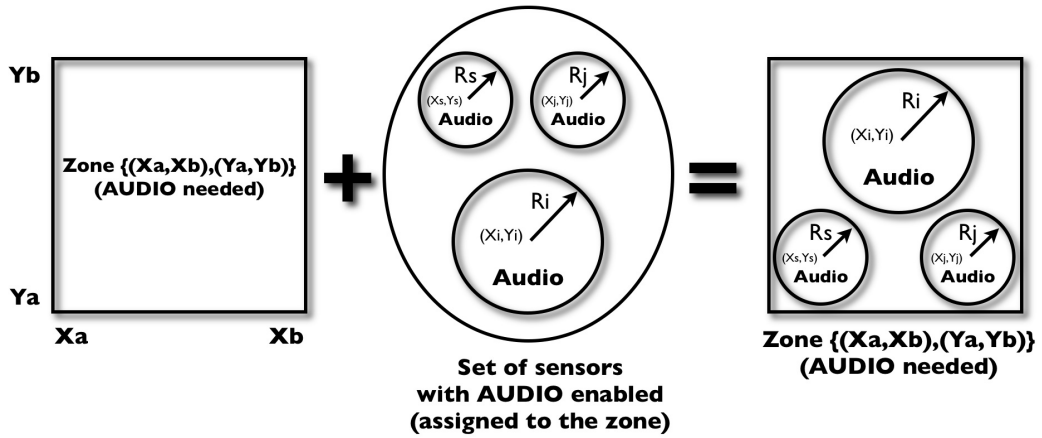



Figure 1.10: Representation of the Sensor Deployment Problem in the final model.

is resolved by applying recursively the model of the multiple knapsack, so in other words we had to create an algorithm that we describe in details into this Section. To understand what we mean with "applying recursively the multiple knapsack model" we will just explain the steps of the implemented algorithm.

**Algorithm:**

1. Subdivide the sensors in classes with the same radius.
2. Order the sensors for decreasing radius and take the first class (so the class with the biggest radius).
3. Subdivide the zone into subzones with side equals to the diameter of the sensors belonging to the class that we are now considering. In this way we will have that the area of a subzone can contain only one sensor belonging to the class currently considered. The area covered by the sensor is approximated with a square (and not anymore with a circle) and it is now exactly equal to the area of the subzone that we are considering now (i.e. $c_j = w_i \qquad \forall i \in N, \forall j \in M$).
4. Solve the multiple knapsack problem with:
   - Knapsacks $\Longleftrightarrow$ Subzones

- Knapsack's cost $\Longleftrightarrow$ Area of a subzone
- Items $\Longleftrightarrow$ Sensors of the first class
- Item's cost $\Longleftrightarrow$ Area covered by sensor
- Item's value $\Longleftrightarrow$ Area covered by sensor

Note that the last two analogies with the multiple knapsack mean that also in this case we are using a particular case of it where $p_i = w_i$ for each sensor (or item).

5. Deploy sensors inside the subzones as states the solution of the multiple knapsack problem just resolved. In particular it is clear that all the sensors of the class will be deployed and none of them will be left out, since the set of sensors on which we are working is the set of sensors assigned to this zone from the "Sensor Assignment" model (which will check that the total area covered by sensors is less than or equal to the area of the zone).

6. Start from the beginning of the algorithm considering the next class of sensor and always the same zone, but this time the zone will be subdivided into smaller subzones having side equals to the diameter of the next class of sensors (which have a smaller radius than the previous class). Moreover we will have to exclude the subzones that are already covered by each of the bigger sensors deployed during the previous cycle.

Let's analyze an example that is also represented in Figure 1.11. If we have two classes of sensors then the algorithm will cycle twice: the first time it will assign the sensors that belongs to the class with the biggest radius to the subzones having as side the diameter of these sensors, the second time it will exclude the subzones already occupied by the sensors of the first class, and then it will assign the sensor of the second class to the new smaller subzones.

### 1.3.4 Modeling considerations

As we already wrote, the first subproblem called "Sensor Assignment" is the hardest to solve but also the most important. The first subproblem can be

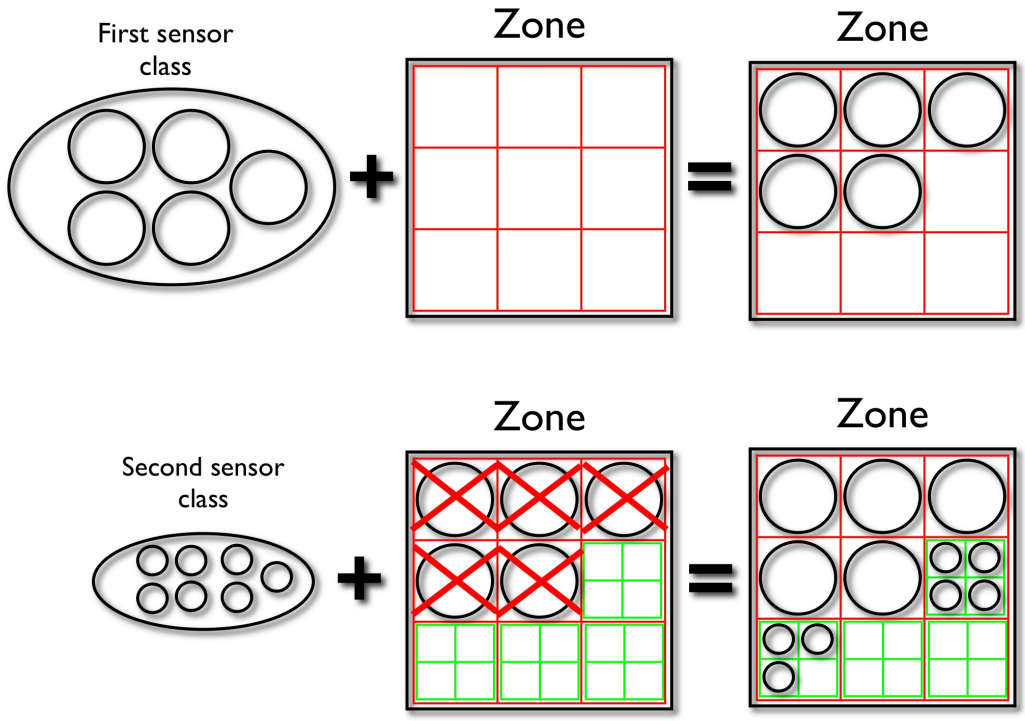



Figure 1.11: An example of application for the Sensor Deployment Algorithm.

considered a "global problem" since it involves the whole map. Only if we have a solution for the first subproblem we can go on to solve the second subproblem that can be considered more a "local problem", since it involves only one zone and a subset of sensors each time.

### Heuristic

Since both the subproblems are quite hard to solve we used an heuristic, necessary so that the "Sensor Assignment" model described in 1.3.3 could work well.

**Heuristic:**
*"The length of the side of each zone and the length of the radius of each sensor have to be a power of two."*

If this is violated there could be the case in which the "Sensor Assignment"

model could insert a sensor in a zone putting it out of shape. An example is represented in Figure 1.12, here we suppose that we are trying to insert the last sensor, with area equal to 7, inside a zone where there are already some sensors deployed and where the remaining area is greater than or equal to 7. If we do not use this heuristic we will have that the constraint 1.21 is respected and all the other constraints would be respected as well, so the solver will solve the problem assigning this sensor to that zone even if it couldn't be inserted. Indeed inserting the sensor in the zone means that we would have to change the shape of the area that it can cover (an oval instead of a circle). Instead the use of this heuristic avoids to have such a situation.

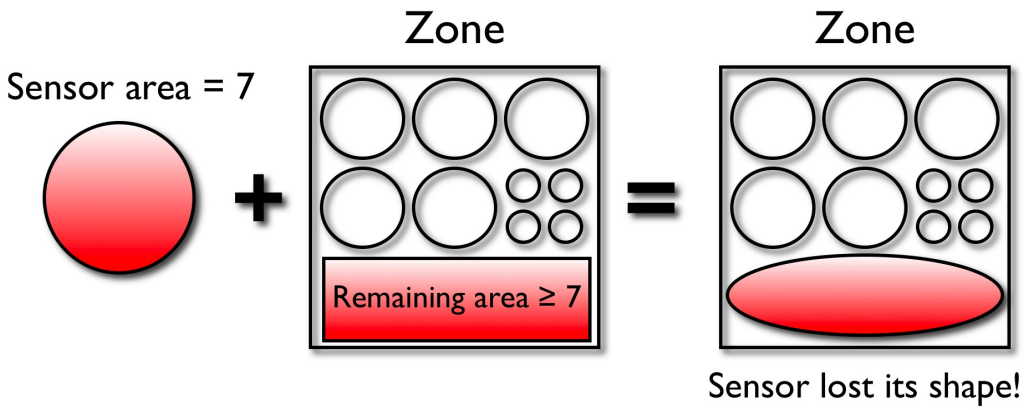



Figure 1.12: The "Sensor Assignment" model without the heuristic.

We apply this heuristic inside the implemented system by using the power of two that is the nearest to the input of the commander. Simply stated the length of the zone side and the length of the sensor radius inserted by the commander using the commander interface will be the power of two that is nearest to the real value inserted by the commander. So for example if the commander inserts "*sensor radius* = 15 meters" then we will use a value of "16".

### Flexibilities of the "Sensor Assignment" model

The "Sensor Assignment" model is very flexible, meaning that it can be well adapted to many different situations.

The first flexibility that we would like to point out is the fact that it is really easy to add to the "Sensor Assignment" model many different type of information. For example if you want to use also sensors that can have the capability INFRARED, you just need to add some constraints and some constants to the model described in Section 1.3.3.

So let's consider the case of "INFRARED", then we will define this constant for each sensor:

$$t_{c_i} = \begin{cases} 1 & \text{if sensor } i \text{ has INFRARED} \\ 0 & \text{otherwise} \end{cases}$$

Now, we will use these convention: A = AUDIO, V = VIDEO, I = INFRARED; so for example an AUDIO and INFRARED sensor or zone will be denoted as A/I, instead an AUDIO, VIDEO and INFRARED sensor or zone will be denoted as A/V/I.
So the types of zones that we can have now become the following:

$\mathbf{M_a} = \{Z_1, ..., Z_e\}$ Set of zones from which "A" is requested.

$\mathbf{M_b} = \{Z_{e+1}, ..., Z_f\}$ Set of zones from which "V" is requested.

$\mathbf{M_c} = \{Z_{f+1}, ..., Z_g\}$ Set of zones from which "I" is requested.

$\mathbf{M_{a,b}} = \{Z_{f+1}, ..., Z_g\}$ Set of zones from which "A/V" are requested.

$\mathbf{M_{a,c}} = \{Z_{g+1}, ..., Z_h\}$ Set of zones from which "A/I" are requested.

$\mathbf{M_{b,c}} = \{Z_{h+1}, ..., Z_l\}$ Set of zones from which "V/I" are requested.

$\mathbf{M_{a,b,c}} = \{Z_{l+1}, ..., Z_m\}$ Set of zones from which "A/V/I" are requested.

The constraints that we will have to add will be:

$$\sum_{i \in N} t_{c_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_c \tag{1.29}$$

$$\sum_{i \in N} t_{a_i} \cdot t_{c_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_{a,c} \tag{1.30}$$

$$\sum_{i \in N} t_{b_i} \cdot t_{c_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_{b,c} \tag{1.31}$$

$$\sum_{i \in N} t_{a_i} \cdot t_{b_i} \cdot t_{c_i} \cdot x_{i,j} = \sum_{i \in N} x_{i,j} \qquad \forall j \in M_{a,b,c} \tag{1.32}$$

From this we can notice that it is really easy to add another capability to the model, and this could be done also in an automatic way. This means that in the future we could implement a method to allow the commander to create new capabilities for the sensors and new information requirements for the zones; and in this way the model could be adapted on the fly to the needs of the commander.

Another consideration is that the "Sensor Assignment" model could be also applied to sensors that can move. We could integrate this new property of the sensor by taking as radius of the area covered by the sensor, the radius of the actual area in which the sensor can move. So we will simply use a bigger radius that takes into account also the case in which the sensor can move form its position. Since the sensor can move, it will have a different position after a while and so it should be necessary to solve again the problem of deploying sensors in an optimal way. This could be a future expansion of this project.

## 1.4 Implementation and Testing

This Section describes the implementation of the system by looking at the technologies used at the implementation of the three components of the system.

Later we also explain the tests done and the performances of our solution.

### 1.4.1 Implementation

#### Technologies Used

It follows a brief description of the technologies used to implement the system. In this Section we refer to Figure 1.3.1, where there is a graphic representation of the system architecture, which is very useful to understand where are located the software components inside the system.

The technologies used are:

**Java 1.6** Since the commander interface and the webservice are written in java they require the Java VM installed on the machines in which they will run.

**Apache Tomcat 6.0.2** This is an application server that allows application written in Java to be executed on the server by a client. This application server represent the platform on which we will install Axis that we need to create the webservice.

**Axis 1.4** This is a platform for developing and deploying webservices written in Java. It is a web application itself that must be installed inside Tomcat.

**choco-1.2.03** This is an open source Java library that is used by the webservice to solve the problem of deploying the sensors inside the zones in an optimal way. This type of library let you apply the Constraint Programming paradigm, by defining variables, domain, constraints and objective function.

#### Webservice Implementation

As we stated above we used Axis to create the Webservice, we chose it because it is really easy to develop new webservices. As a matter of fact we just

needed to write your own Java code and insert our packages inside Axis. Then we created two files of configuration to let Axis know that it had to deploy a new webservice. Furthermore the installation of Axis, which runs inside the Apache Tomcat application server, is quite easy to accomplish in a limited amount of time.

We now give a brief overview of the Java classes that implement the Webservice. This webservice is composed by one package "deploySensorsService" that contains a file "MyService.java" which actually implements the webservice, and a subpackage "deploySensorsService.solver" that contains all the classes which implement the CSP solver using the CHOCO library.

- Let's consider the package "deploySensorsService":

  **MyService.java** This class implements the webservice: the method "computeDeployment" performs the deployment of the sensors inside the zones, the other methods are used to return to the client the actual sensor deployment.

  The thing that is very important is that once the CSP solver has solved the problem, then the solution will be stored inside the webservice. So when the BF2 server will ask for the current optimal deployment, the webservice will return the value of the "static" variables which contains the data about the optimal deployment.

- Let's now consider the subpackage "deploySensorsService.solver", where the class that actually solve the problem is "DeploySensors.java" which uses "ZoneDeploy.java" as an auxiliary class. The other classes are data structures and auxiliary methods used by these two main classes:

  **DeploySensors.java** This class solves in sequence, before the *Sensor Assignment* problem (Section 1.3.3) and then the *Sensor Deployment* problem (Section 1.3.3). This last subproblem is solved using the class "ZoneDeploy".

"DeploySensors.java" reflects the global structure of the main problem that is divided into two subproblems: the Sensor Assignment and then the Sensor Deployment problem. The implementation of the model is the direct translation of it into CHOCO constraint language, and because of this also the implementation benefits of the flexibilities described in Section 1.3.4.

**ZoneDeploy.java** This class solves the "Sensor Deployment" problem for each zone considering only the sensors assigned to the zone. This problem is solved by applying the algorithm described in Section 1.3.3.

**Sensor.java** This is a data structure that represents the sensor and its properties. It could be considered as a primitive ontology for the object Sensor.

**CoveredArea.java** This is a data structure that represents the zone selected by the commander and the information that is required from it. Also this could be considered as a primitive ontology for the object Zone.

**SubArea.java** This class represents a subzone created by the division of a zone into smaller zones, this class is used in the algorithm that solves the "Sensor Deployment" problem.

### Commander's Interface Implementation

The commander's interface is actually a command line interface written in Java, and it sends parameters to the webservice via SOAP messages using particular Java libraries provided by Axis. The commander interface is composed by one package "deploySensorsClient" which contains a file "MyClient.java" and a subpackage "deploySensorsClient.structures". The first is the main class of the application and it implements the command-line interface, the second contains all the data structures used by the interface to perform its tasks (i.e. the same data structures used by the Webservice solver such as Sensor.java or CoveredArea.java).

- So the package "deploySensorsClient" contains:

  **MyClient.java** This class implements the Commander's interface. the commander can set the parameters of the problem (sensors and zones) and then these will be sent to the webservice where the problem will be solved. Finally, the solution will be sent back to the commander's interface that will show to the commander the exact locations in which all sensors will be deployed.

  Note that inside this class it is implemented the heuristic that we described in the Section 1.3.4. In fact when the commander inserts a length value for the zone side or for a sensor radius, the interface will automatically compute the power of two that is the nearest to the number inserted. This will be the real value used to solve the problem.

### "Battlefield 2 Mod" Implementation

As explained in Section 1.1.4, Battlefield 2 allows to develop your own plug-ins for the server, these plug-ins are called "mod" and they are written in Python. The real core of the Mod is implemented inside the file "scoringCommon.py". We used also other utility modules that are "Utils.py" and "Defines.py" which were taken from the mod "PlanAndPlay".

**scoringCommon.py** This file is the core of the mod: It asks to the webservice for the current sensor deployment (that had been set before by the commander) and then it creates Sensitive Area inside the map simulating the behaviour of real sensors.

The issue is that once we created sensors inside the map, we cannot delete them on the fly while there are still other players inside the map since the game clients asks for the sensitive area that they have to create inside the local map only when they join the game. So we had to work out a mechanism that could delete old sensors and deploy the new sensors belonging to the solution of a new problem set by the commander:

**Creating sensors:** Each time that the first player join the server loading the map, the Battlefield 2 server will send a request to the webservice for the current optimal deployment, and then the Battlefield 2 server will create the sensors on the map

**Removing sensors:** When the last player disconnects from the current game, the effect is that the map and all the python code will be reloaded so that the old sensors created inside the map will be removed. When the first player will connect to the server and join the game, there will be again the same sequence of actions described in **Creating sensors** and the sensors will be deployed on a clean map.

### 1.4.2 Testing and Evaluation

Since the most part of the time was spent to develop the model of the problem and then to implement the whole system, there was not so much time left to perform tests and evaluate its performances.

Anyway we carried on some interesting tests that highlighted the performances of the model implementation. Note that we are talking about the performance of the implementation and not about the performances of the model, since we know already that the problem is NP-complete, i.e. the solving time will grow exponentially with the number of parameters used.

During these tests we focused on trying to identify which were the parameters of the problem that were increasing the solving time the most, and we found out that these parameters are: the number of sensors and of zones with multiple capabilities, and also the relative dimension of the sensors compared to the dimensions of the zones[15]. Note that the time spent to solve a problem will not depend from the size of the map thanks to the model, since we are only considering the number of zones selected by the commander.

[15]Meaning that the problem is harder to solve if the sensor area is a lot smaller than the zone area.

We proceed by finding some parameters for the problem that could constitute a base test case that we could later modify matching our requirements. This base test takes as parameters 15 sensors of which 5 AUDIO sensors, 5 VIDEO and 5 A/V; each class of sensor has a different radius that is 64 meters for AUDIO sensors, 64 for VIDEO and 32 for A/V. Moreover it uses 6 zones all with the same side of 128 meters[16] and with different types of information needed: two AUDIO zones, two VIDEO and two A/V. It takes more or less 20 seconds to the solver to solve this problem.

Now we consider a variation of this test case decreasing the number of A/V sensors, i.e. we will have 10 AUDIO sensors, 3 VIDEO sensors and only 2 A/V sensors, the solving time is only 1 second, a lot better than the previous time.

Finally we considered another variation by increasing the dimension of the sensor radii and of the zone sides but keeping the same ratio between them that was used in the base test case. So we will have 5 AUDIO sensors with 128 meters of radius, 5 VIDEO sensors with radius 128, and 5 A/V with radius 64; instead the side of each of the 6 zones will be 256 meters. This problem takes 20 seconds to be solved that is exactly the same time of the base test case.

We surmised that if the ratio between the dimensions of the sensors and of the zones remains the same then the time taken to assign sensors to zones will be the same.

An important issue rises when there is no solution to the problem and the solver has to understand it. If the problem is "easy" the time to wait will be very short and it will answer that there is no feasible solution, but if there are many sensors with small radius and zones with big side, then it will take a lot of time, and it could also go on indefinitely trying to find a solution. This is understandable since we are facing a strongly NP-complete problem.

[16]Note that the side is equal to the diameters of the AUDIO and VIDEO sensor so one of these sensors will fit exactly one zone.

## 1.5 Conclusion and Future works

This Section presents some conclusions to our project, discussing which were our expectations at the beginning of the project and how things actually went. We also present possible extensions and improvements to our system as future work.

### 1.5.1 Conclusion

At the beginning of this project we were not really concerned about the development of a model but we were more worried about the actual implementation, in particular about how we could represent sensors in Battlefield 2 and how to integrate everything inside this virtual environment. At the end, instead, it turned out that the hardest part of the project was to develop the right model for the problem that we were facing, and after this step the implementation was quite straightforward, at least for the solver inside the webservice. In any case we had to spend much time on the design of the webservice and on the commander's interface, instead with regards to Battlefield 2 Mod server, we have been very lucky since the parallel project "Plan and Play" (introduced in Section 1.2.2) had worked a lot with Battlefield 2 and so we could re-use some of the knowledge developed in that project.

In conclusion the goal of the project was successfully met and the model that we developed for the problem seems to be a real innovation in this field.

### 1.5.2 Future works

There are many future works that could be done starting from this project, but always keeping as basis the same model described in this document without changing it very much, since as we showed it is very flexible.

### Improving solver: Relaxed Constraints

As we discussed in Section 1.4.2 the solver could spend a lot of time to find the solution for a problem with many sensors and zones, or it could go on indefinitely trying to understand if it exists a solution. To improve the solver performances, we could apply a technique that uses the same model but relaxes the constraints defined in the problem.

### Objective function improvement

In the future we could also try to develop a better objective function, by considering for each item $i : p_i \neq w_i$ , that are constants that we met in Section 1.3.3, and so we could maximize the total value of the sensors assigned to the zones. In this way a new objective function could maximize the total area covered by sensors, minimize the number of sensors used and at the same time maximize the value of the sensors chosen.

We could also create many different objective functions and then let the decision of which to use to the commander, depending on the requirements of the particular mission.

### Dealing with multiple mission

An interesting feature of this model is that it can already deal with multiple missions[17]. In fact, for example if there are two different commanders for two different missions, then they will have the same map and the same set of sensors available to share between the two missions, but they will mainly select different zones. It is enough to make a join of the two sets of zones and to pass them together with the set of common sensor to the problem solver, and it will solve the problem. Actually there could be the need of some minor adjustments to the model but it should be really straightforward.

[17]Here we assume that missions can use the information coming from a sensor at the same time. So we don't have the problem to decide to which mission we have to assign a particular sensor.

### Integration with "Plan And Play"

This project can be integrated with "Plan and Play" (PnP), described in Section 1.2.2. In fact PnP, as we stated previously, integrates a planner with Battlefield 2, and this planner receive in input a plan. To integrate PnP with this project it is enough to write a plan (for the planner) to realize the optimal deployment of the sensors by sending soldiers to place sensors in the optimal locations chosen by the solver. So in this case the planner will have as objective the optimal deployment and it will say to the soldiers how to reach safely the optimal locations to place sensors.

# Chapter 2

# Sensor Assignment to Competing Missions

## 2.1 Introduction and Motivations

The sensor-mission matching problem is a very complex problem that arises often in a military environment, when we have to deal with a sensor network and multiple competing missions. A sensor network consists of a large number of sensing devices that are able to gather information about the facts happening in their surroundings. Usually the network of sensors is already deployed in the field and it is supposed to satisfy the information requirements of multiple missions. Missions can be competing for the same network resource, and so we need to find a schema to match sensor resources to missions. In every scenario a single sensor will have a different degree of *utility* for a certain mission, since it will offer to it different quality/quantity of information depending on some factors (such as distance from a certain point where the task related to the mission is located). Missions may have different degree of importance (*profit*) and different levels of required utility from the sensor network (*demand*).

Usually the demand of utility of each single mission is uncertain, for example because of the unknown conditions on the battlefield (e.g. weather, sensor network damaged, etc.). A concrete example is given by the case in which a mission needs some video devices but we don't know the weather conditions

and so the visibility range; in such a case the number of video sensing devices is variable and this means that its utility demand can be considered variable in a certain range. So it is reasonable to consider that the demand of each mission is the maximum quality/quantity of information that can be require from the sensor network. In this situation it is important to assign to the mission a subset of sensors that will give to the mission a total utility that will remain under its demand, since the mission could have a real information requirement that is much less than the one expressed with the demand of the mission. This means that it is not allowed to "waste" even a little part of the informations that the sensor network can collect. Indeed in a common real scenario it is not allowed to assign to the mission a number of resources that will supply the mission with more information quantity or quality than the one needed as maximum. Therefore in our model we consider the demand of a mission as a budget of required utility not to be exceeded while deciding the "best" assignment of sensors.

Now the issue is to choose what is meant by "best assignment of sensors to missions". Since a sensor will contribute with a different utility to each mission, we can state that each sensor will bring a different benefit to each mission, depending on: the fraction of the mission's demand that the sensor will satisfy, and also on the importance of the mission itself. Since the benefit that each sensor can bring to a mission is strongly correlated to the utility that the sensor has for the mission, in our model we will try to maximize the total benefit that an assignment of sensors can bring to all the missions by encouraging the utility to go where it is most helpful, for this reason we chose for this model the name "Sensor Utility Maximization".

In this Chapter, we define the *Sensor Utility Maximization* (SUM) problem and show that it is equivalent to a more general problem called *Generalized Assignment Problem* (GAP) that is **NP**-Complete. This more general problem is well studied in the literature, and as a matter of fact we implemented an existent $(2 + \epsilon)$-approximation greedy algorithm from [5], improving its performances while saving memory space and computational time. We also tried to implement new greedy algorithms that in many cases have comparable performances. Furthermore we used a linear programming solver (LP solver) to

check if it was possible to obtain a good solution in a reasonable time for the size of our problem instance.

The rest of this Chapter is organized as follows. Section 2.2 discusses some related work in sensor assignment problems, emphasizing the differences and similarities with our approach. In Section 2.3 we formally define the *Sensor Utility Maximization* problem and study its computational complexity, showing that it is equivalent to the GAP. In Section 2.4 we describe how we solved the problem using an LP solver, and we propose our three greedy algorithms. We give also a description of how we implemented efficiently the $(2 + \epsilon)$-approximation greedy algorithm described in [5]. In Section 2.5, we evaluate the performances of the proposed solutions using simulations. Finally, Section 2.6 concludes the paper and outlines some ideas for future work.

## 2.2 Related Work

There has been a lot of work recently developed on the sensor-mission assignment problem. For example, [4] approaches the assignment problem using the notions of utility and cost. Here they try to find a solution that maximizes the utility while staying under a predefined budget, but they use a cost model based on energy consumption which is different from our cost model based on the utility demand of every mission. Another important difference is that in our work we consider multiple missions with different priorities that could possibly compete for the same subset of sensors, instead in [4] the different tasks do not have a varying priority, so they are considered to be equally important.

A problem that is strongly correlated to SUM is presented in [3] and [8], which is called the *Semi-Matching with Demands (SMD)* problem. It models the problem of assigning sensors to multiple competing missions as a bipartite graph where nodes can be sensors or missions. Each mission is associated with a demand value, that is the utility demand required by the mission to be satisfied, and a profit value, that represents the importance or priority of the mission/task; each sensor-mission pair is associated with a utility offer (possibly 0).

The similarities with the definition of the SUM problem are evident, indeed SUM can be modeled too as a bipartite graph that resembles exactly the same graph described in [3] and in [8]. But there are also many important differences. First of all SUM gives a different meaning to the *demand* of a certain mission, i.e. it is intended as an upper bound on the utility requested by a mission, since the utility demanded by a mission is usually very uncertain, as we noticed in Section 2.1. Anyway the most important difference with our work is that in SMD model the goal is a sensor assignment that maximizes the profits of the satisfied missions, with no credit for partially satisfied missions. Instead SUM goal is to assign sensors to missions in which they are most useful, without caring about the particular satisfaction of each particular mission. SUM considers only the "global happiness" of the set of mission and not of every single mission, in such a way that there is no waste of information gathered by the network.

In this way we loose the concept of satisfaction of a single mission, since we do not ensure that the amount of sensor utility assigned to a single mission will satisfy the mission needs of information, but we are now able to assign sensors to missions in such a way that each sensor will gather the finest informations for a certain mission, and even if this will not be enough to satisfy the mission, in every case this will be an information of great value for the mission. So we are leaving in the background the exact utility demand of a mission, and giving more importance to the quality of information acquired by the network. In other words SUM guarantees a very high global QoI (Quality of Information) for the entire sensor network.

Another thing to observe is that SMD model gives much more importance to the *profit* (or importance) value of every single mission, since it uses this parameter to decide which are the first missions that have to be satisfied. SUM instead uses this parameter only to scale the utility that the sensor will bring to the mission, as we will see in Section 2.3. It is because of this that SUM model could be chosen, instead of SMD, in cases in which the importance of a mission is very uncertain. In fact in many real life scenarios we have noticed that the profit value (i.e. importance) of a single mission is never really known, to determine it exactly we should have an absolute scale that allows us to ex-

press the importance of a mission in comparison with other mission profits. This works for standard missions - for example in the case of an hostage rescue mission that will probably be more important than a mission to detect a target - but when we deal with more complex missions this clear classification becomes more undefined.

SUM can also be viewed as a generalization of a model developed for the sensor deployment problem, introduced in [12] and also in Chapter 1. The sensor deployment problem is solved in two steps: first, sensors are assigned to zones, and finally sensors are deployed inside each zones to which they were assigned. The first subproblem (described in Section 1.3.3) is modeled as an extension of the multiple knapsack problem which can be considered the base for the model presented in this paper.

In the extended multiple knapsack model the sensors have some capabilities associated and they can only be assigned to zones that have a request of information compatible with the capabilities of the sensor[1]. Each sensor is also associated with a *coverage area*, and each zone has a certain *required area* to be covered. The main constraint in this model is that the total area covered by the set of sensors assigned to the zone must be less than or equal to the area of the zone. The goal is an assignment of sensors to zone that maximize the total area covered by the entire set of sensors. It is clear that SUM can be seen as a generalization of the extended multiple knapsack model: the coverage area of a sensor in [12] can be compared to the utility offered by a sensor to a mission in this model, but with the difference that the utility offered can possibly differ for every mission.

As we will show in Section 2.3, SUM is equivalent to a more general problem called *Generalized Assignment Problem* (GAP), often used to solve resource allocation problems under budget constraints. There exists a lot of literature about this, in particular in [5] and in [7] the authors propose efficient

[1]So for example an AUDIO sensor can only be assigned to a zone that requires AUDIO; but an AUDIO/VIDEO sensor can be assigned to an AUDIO zone, since it can cover the need of AUDIO informations.

approximation algorithms which solve the GAP with a certain approximation guarantee and in a reasonable computational time[2]. In Section 2.4, we will describe our implementation of the algorithm described in [5] that we improved in terms of effective computational time and memory usage.

It is very important to note that, to the best of our knowledge, this is the first time that GAP is applied to solve a sensor assignment problem, and more in general a sensor network resource allocation problem.

## 2.3 Sensor Utility Maximization Problem definition

SUM can be seen as a complete weighted bipartite graph, in which the vertex sets is composed by sensors $S = \{S_1, \ldots, S_n\}$ and by missions $M = \{M_1, \ldots, M_m\}$ (see Fig. 2.1). Each mission $M_j$ has a positive-valued demand $d_j$, which indicates the max utility (or quality of information) that a mission could require. A mission has also an importance (or profit) $p_j$ associated with it, that represents the mission's priority.

Each edge $(S_i, M_j)$ is associated with two values $(e_{ij},\ p_{ij})$. The first $e_{ij}$ indicates the utility that $S_i$ could contribute to $M_j$ if it is chosen to assign sensor $S_i$ to mission $M_j$. The second parameter $p_{ij}$ is the benefit (or profit) that $S_i$ could bring to mission $M_j$, if this pairing were chosen. The parameter $p_{ij}$ includes in it the concept of demand and of importance of a mission, since it holds always the following equality: $p_{ij} = e_{ij}/d_j \times p_j$.

In other words the benefit that a sensor $S_i$ can bring to mission $M_j$ is given by the fraction of demand that the sensor will satisfy, scaled by the importance of a mission. This last multiplication for the mission importance allows us during the assignment to favor high priority missions, for example if we have to assign a sensor which can contribute with the same fraction of utility $(e_{ij}/d_j)$ to two different missions, then we will assign it to the mission with the highest profit $p_j$ since, as we stated before, the benefit $p_{ij}$ contains the fraction of utility contribution scaled by $p_j$.

[2]Usually the computational time is correlated to the approximation degree desired.

**Our goal** is an assignment of sensors to missions that maximizes the total benefit (or profit) of the sensor network by sending the utility where it is most helpful, so that each sensor is assigned to only one mission, and that the total utility assigned to a mission remains under its demand[3] $d_j$. So using the parameters defined above, we want to maximize a sum of all the $p_{ij}$ of each sensor $S_i$ assigned to mission $M_j$.

Now we can define the problem formally:

**Instance:** Given a bipartite graph $G = (S, M, MP, E, SP)$,
where $S = \{S_1, \ldots, S_n\}$ is the vertex set of sensors, $M = \{M_1, \ldots, M_m\}$ is the vertex set of missions, $MP = \{p_1, \ldots, p_m\}$ is the collection of mission profits, $E = \{(e_{ij}) : \forall \text{ edges } (S_i,\ M_j)\}$ is the collection of sensor-mission utility associated with the edges $S \times M$. Finally, $SP = \{(p_{ij}) : \forall\ (S_i,\ M_j)\}$ is the collection of sensor-mission profits associated with the edges, note that $p_{ij} = e_{ij}/d_j \times p_j$.

**Goal:** Find a semi-matching $F \subseteq S \times M$ (i.e. no two chosen edges share the same *sensor*), in which $\sum_{(S_i,M_j)\in F} p_{ij}$ is maximized for the entire sets S of sensors and M of missions, and where $\sum_{(S_i,M_j)\in F} e_{ij} \leq d_j$ for each mission $M_j$.

It is probably easier to understand the problem in its Integer Programming formulation. In the formulation we use one decision variable called $x_{ij}$, indicating if sensor $S_i$ is assigned to mission $M_j$. For each mission $M_j$ we require that the sum of utility received by $M_j$ is at maximum the value $d_j$.

**Maximize:** $\sum_{j=1}^{m} \sum_{i=1}^{n} p_{ij} x_{ij}$ , where $p_{ij} = e_{ij}/d_j \times p_j$.

**Such that:** $\sum_{i=1}^{n} x_{ij} e_{ij} \leq d_j$, for each mission $M_j \in M$,

$\sum_{j=1}^{m} x_{ij} \leq 1$, for each sensor $S_i$, and

$x_{ij} \in \{0, 1\}$, for each variable $x_{ij}$

[3]As we explained above the demand is intended as the max utility required by a mission, since the effective demand of utility is uncertain.

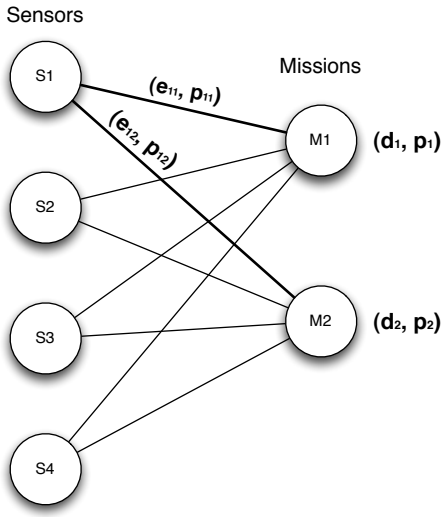



Figure 2.1: Modelling *Sensor Utility Maximization* as a bipartite graph.

We notice immediately that there is a strong relationship with the classic problem called Multiple Knapsack Problem and in specific with the model described in [12] and in Section 1.3.3. More in general, we know from the literature that the Multiple Knapsack Problem is a particular case of the *Generalized Assignment Problem* (GAP), where we use different weights and profit values for each item with respect to every bin (or knapsack).

**Proposition 2.3.1** *The SUM problem is the Generalized Assignment Problem (GAP), hence it follows that SUM is* ***NP****-Complete.*

*Proof:*

To show that SUM is identically the same of the GAP, it is enough to observe the similarities between the two Integer Linear Programming formulations.

Anyway it is perhaps easier to explain before the Generalized Assignment Problem with a non mathematical definition. So using simple words, we have the **Maximum Generalized Assignment Problem** when:
Given a set of bins with *capacity* constraint and a set of items that have a possibly different *size* and *value* for each bin, we want to pack a maximum-

valued subset of items into the bins[4].

Now it is immediate to understand the following Integer Linear Programming formulation of the GAP. About the notation, we indicate the generic item with an "$i$" where $i \in I = \{1, \ldots, n\}$, and the generic bin with a "$j$" where $j \in J = \{1, \ldots, m\}$; for each bin its capacity is denoted with $c_j$. Finally the size and the value of each item, with respect to every bin, are respectively: $w_{ij}$ and $p_{ij}$. We will use a decision variable called $x_{ij}$, indicating if item $i$ is assigned to bin $j$.

**Maximize:** $\sum_{j=1}^{m} \sum_{i=1}^{n} p_{ij} x_{ij}$

**Such that:** $\sum_{i=1}^{n} x_{ij} w_{ij} \leq c_j$, for each bin $j$

$\sum_{j=1}^{m} x_{ij} \leq 1$, for each item $i$

$x_{ij} \in \{0, 1\}$, for each variable $x_{ij}$

Now the SUM can be reduced to the GAP (and viceversa) in a polynomial time, it is enough only to equalize the name of the parameters of the models described above: $w_{ij} = e_{ij}$, $c_j = d_j$ and $p_{ij} = p_{ij}$. It follows that the GAP and the SUM are the same problem since one can be reduced to the other with a simple equality between the parameters of their models.

More precisely SUM is an instance of GAP in which there is a strong correlation between the *value* and the *size* of each item (which are sensors in SUM). Indeed in the Sensor Utility Maximization model we have that the *size* of each item is $e_{ij}$ and instead the *value* is $p_{ij} = e_{ij}/dj \times p_j$, so it is clear that $e_{ij}$ and $p_{ij}$ are directly proportional in SUM.

Now since GAP is known to be an **NP**-Complete problem, and since SUM and GAP are the same problem, thus it follows that also SUM is **NP**-Complete. □

Comparing the SUM model described above with the *Semi-matching with Demands* (SMD) model described in the related works (Section 2.2) we can observe the strong relation between them. We report here for purpose of comparison the SMD model:

[4]For a deeper discussion on GAP, see [5] and [7].

**Maximize:** $\sum_{j=1}^{m} p_j y_j$

**Such that:** $\sum_{i=1}^{n} x_{ij} e_{ij} \geq d_j y_j$, for each mission $M_j$

$\sum_{j=1}^{m} x_{ij} \leq 1$, for each sensor $S_i$

$x_{ij} \in \{0, 1\}$, for each variable $x_{ij}$

$y_j \in \{0, 1\}$, for each variable $y_j$

As we clearly stated above SUM and SMD are solving the problem of sensor assignment but with two completely different approaches. The first, SUM, is trying to find a solution that maximize the "happiness" of the whole sensor network; the second, SMD, has the goal of finding a solution that will maximize the number of most important missions satisfied looking only at the "happiness" of each single mission.

Anyway the two models are using more or less the same parameters. The values that they have in common are for the missions $p_j$ as the importance, $d_j$ as the demand, and instead for the sensor-mission pairs $e_{ij}$.

An interesting difference is in the meaning that the two models give to the demand of a mission $d_j$. SMD states that the demand is the minimum utility required by the mission to be satisfied, SUM instead defines the demand as the maximum utility required by a mission, and in the latter there is no concept of satisfaction of a mission. Our model is, as a matter of fact, based on the assumption that the effective utility required by a mission is uncertain, and so we can only deal with a range of value in which the effective demand could fall into.

Also SUM wants to take into account the importance of a mission while assigning sensors giving the possibility to the most important missions to have the priority on the resources of the sensors, as SMD is doing. SUM tries to include this concept inside the additional parameter $p_{ij}$, in particular it represents the benefit that the sensor $S_i$ will bring to the entire sensor network if it is assigned to mission $M_j$. The goal of our model is therefore an assignment that maximizes the total sum of the $p_{ij}$.

Both SUM and SMD are models that can be used to solve the sensor assignment problem, but depending on the real situation we will decide which

is the best model to use.

In conclusion, it is better to use SUM when:

- There is *high uncertainty* about the effective utility *demand* of missions (as we stated in 2.1)

- There is *high uncertainty* about the effective *importance* of missions (as we stated in 2.2)

- All the missions have more or less the *same importance (or priority).* Indeed when all the missions have comparable priority, it does not matter to choose which missions to satisfy as SMD, but instead it really matters to maximize the utility of the entire sensor network that is what SUM is doing.

- Another interesting scenario in which SUM could be used instead of SMD is the case in which there are many sensors which have a utility offer $e_{ij}$ that is very similar to the demand $d_j$ of each mission.
  Let's analyze a concrete example: suppose that we are given two missions respectively with demands $d_1 = 1$ and $d_2 = 1$, and suppose we have a network composed by two sensors with offered utility $\{e_{11} = 0.9, e_{12} = 0.9\}$ for the first sensor $S_1$, and $\{e_{21} = 0.9, e_{22} = 0.9\}$ for the second sensor $S_2$. In this case SMD will assign $S_1$ and $S_2$ to only one mission, let's say $M_1$, leaving $M_2$ completely unsatisfied; instead SUM will assign each sensor to a different mission, so let's say $S_1$ to $M_1$ and $S_2$ to $M_2$. It is trivial to understand that the first solution wastes a lot of utility offered by the sensor network and it leaves uncovered a mission that even if it wouldn't be entirely satisfied, it could have been almost satisfied. The second solution instead does not waste any sensor utility and it makes both mission almost satisfied, and since the assumption of SUM is that the utility demand $d_j$ is the maximum utility demand that a mission could require, then it could be the case that the real demand of both missions is less than 1 and in this way we would have satisfied both missions.

## 2.4 Centralized solutions

In this work we describe only centralized approaches to solve the sensor-mission matching problem, distributed solutions are possible but are not described here. In a centralized approach all the decisions are made in a base station which is a special control node in the network. The negative point compared to the distributed approach is that a centralized solution needs first to collect all the information in a single node of the network and this requires an higher number of exchanged messages to configure the network. Anyway the benefit to use a centralized approach is that we have a global view of the network and because of this we can probably find a better solution.

We developed different ways of solving the SUM problem: we used an Integer Linear Programming Solver (lp-solver), we also created four Greedy Algorithms inspired by the algorithms contained in [3] and in [8], and finally we improved the performances of the $(2+\epsilon)$-Approximation Greedy Algorithm conceived in [5].

### 2.4.1 Integer Linear Programming Solver

We first utilized an open source Integer Linear Programming (ILP) solver called *LP_SOLVE* to check if for the size of our instance we could obtain an optimal or at least a good solution in a reasonable time, anyway the expectations from this approach were not very high since SUM is **NP**-Complete, as we proved in Proposition 2.3.1.

This ILP-solver applies the well known Branch-and-Bound algorithm to find a solution to Integer Linear Programming problems, i.e. when there are integer variables, otherwise it uses an implementation of the simplex algorithm when dealing only with real variables.

Many expedients were used to push *LP_SOLVE* at the best of its possibilities, like for example presolving the problem. The presolve function is built into *LP_SOLVE* and it analyzes the instance of the problem before applying the Branch-and-Bound algorithm. The output of this function is the same instance of the problem but with a reduced number of constraints and variables,

so easier to solve.

Despite all the expedients taken while using *LP_SOLVE* to solve a medium sized instance of SUM problem, i.e. with 500 sensors and 50 missions, the computational time was too high. Because of this the only way was to use *LP_SOLVE* was with a **timeout** of 10 seconds, after which the Branch-and-Bound algorithm is stopped. If the algorithm has found a feasible solution then it returns the best feasible solution found, that is the solution with the highest value of the objective function. We modified the behavior of *LP_SOLVE* in such a way that if the Branch-and-Bound algorithm does not find any feasible solution before the timeout, then it will run again with an increasing timeout until it finds the first feasible solution which will be the returned solution.

### 2.4.2 Greedy Algorithms

In this Section we give four simple greedy algorithms to find a good (thought not always optimal) solution to the *Sensor Utility Maximization* problem. This four algorithms were inspired by the algorithms developed in [3] and in [8] to solve *Sensor-Matching with Demands (SMD)* problem, but the general behavior of this simple greedy algorithms recall the classic algorithms developed to solve knapsack-style problems. For these algorithms we don't give a theoretical proof of the degree of approximation of the solution found, we only test them with different instances of our problem and in Section 2.5 we show that they guarantee a very good solution in practical test cases. Anyway in Section 2.4.3 we show an algorithm that can ensure a certain degree of approximation that can be proved theoretically.

The point of using a greedy algorithm is that, if they are well conceived, they can guarantee a very good approximated solution in a polynomial time, that is what we want when we deal with an **NP**-Complete problem.

#### Mission-side greedy

The first greedy algorithm that we consider (Algorithm 1) takes missions one by one and assigns sensors to them. The approach is to sort missions in order of decreasing importance (or profit) $p_j$, then for each mission it sorts the available

sensors in decreasing order of utility offered to that mission and assigns them until the total utility cumulated by the mission stays under the demand $d_j$ of the mission. The complexity of this algorithm is $O(mn \log n)$, with $n$ sensors and $m$ missions. For this to be true $m$ must be $O(n \log n)$.

**Algorithm 1** Mission-side Greedy

```
1: sort the missions in order of decreasing p_j
2: for each mission M_j in sorted order do
3:    sort unused sensors in decreasing order of e_ij
4:    for each unused sensor S_i in sorted order do
5:       if e_ij + total utility cumulated by M_j ≤ d_j then
6:          assign S_i to M_j
7:       end if
8:    end for
9: end for
```

### Sensor-side Greedy

The second algorithm (Algorithm 2) is a greedy algorithm from the point of view of the sensor. The algorithm assigns each sensor to the mission $M_j$ to which the sensor is most useful, i.e. to the mission that maximizes $p_{ij}$. The complexity of this algorithm is $O(nm \log m)$, where "$m \log m$" is given by the fact that we have to find the mission $M_j$ that maximizes $p_{ij}$.

**Algorithm 2** Sensor-side Greedy

```
1: M ← {M_1, ..., M_m}
2: for each sensor S_i in arbitrary order do
3:    M_k ← maxarg_{M_j ∈ M}{p_ij} (where p_ij = e_ij/d_j × p_j)
4:    if e_ik + total utility cumulated by M_j ≤ d_j then
5:       assign S_i to M_k
6:       M ← M − {M_k}
7:    end if
8: end for
```

### Ordered Sensor-side Greedy

This algorithm (Algorithm 3) is an improvement of the previous algorithm, indeed the main body is exactly the same of the Sensor-side Greedy. The only difference is that before processing sensors it sorts them in decreasing order using as parameter the maximum profit offer of each sensor, i.e. $max\{p_{ij}\}$ between all the missions $M_j$ to which the sensor can contribute. The complexity is still $O(nm \log m)$ if $n$ is $O(m \log m)$, otherwise it is $O(nm \log m + n \log n)$. This happens because now the algorithm is also doing a preprocessing of the sensors, and the best sorting algorithm has complexity $O(n \log n)$.

**Algorithm 3** Ordered Sensor-side Greedy

```
1: sort the sensors in order of decreasing max{p_ij}
2: M ← {M_1, ..., M_m}
3: for each sensor S_i do
4:    M_k ← maxarg_{M_j ∈ M}{p_ij} (where p_ij = e_ij/d_j × p_j)
5:    if e_ik + total utility cumulated by M_j ≤ d_j then
6:       assign S_i to M_k
7:       M ← M − {M_k}
8:    end if
9: end for
```

### Ratio Sensor-side Greedy

The last simple greedy algorithm is another modification of the Sensor-side Greedy, and it is called Ratio Sensor-side Greedy (Algorithm 4). It is very similar to the Ordered Sensor-side Greedy since it orders the sensors before processing them, but the difference is that the sensor are ordered by decreasing $\max\{p_{ij}/e_{ij}\}$. Simply stated, we try to assign first the sensors that have the biggest offered profit and the smallest utility offer to the mission. This is the classic approach of knapsack problems where it is usual to assign first items that have a high profit value and a small size, so that it is possible to maximize the total profit value while packing the highest number of items into the knapsack since we insert small items before.The complexity of this algorithm is the same of the Ordered Sensor-side Greedy (Algorithm 3).

As we will see this in Section 2.5 this will turn out to be one of the worst algorithms for our problem in terms of goodness of the solution. Indeed in our specific case we are dealing with $p_{ij}$ and $e_{ij}$ strongly correlated, in particular we will have the following: $\max\{p_{ij}/e_{ij}\} = \max\{p_j/d_j\}$, since $p_{ij} = e_{ij}/d_j \times p_j$. So the sensors will be ordered using as parameter $\max\{p_j/d_j\}$ that doesn't really depend from the sensor but only from the set of mission, so we can conclude that the preprocessing of sensors is useless. We reported here this algorithm since in the future there could be cases in which we could have the need to use a profit offer value ($p_{ij}$) and a utility offer value ($e_{ij}$) completely uncorrelated. In this scenario this algorithm may work really well.

**Algorithm 4** Ratio Sensor-side Greedy

```
1: sort the sensors in order of decreasing max{p_ij/e_ij}
2: M ← {M_1, ..., M_m}
3: for each sensor S_i do
4:    M_k ← maxarg_{M_j∈M}{p_ij} (where p_ij = e_ij/d_j × p_j)
5:    if e_ik + total utility cumulated by M_j ≤ d_j then
6:       assign S_i to M_k
7:       M ← M − {M_k}
8:    end if
9: end for
```

### 2.4.3 $(2+\epsilon)$-Approximation Greedy Algorithm Improved

As we showed in Proposition 2.3.1 the SUM problem is the Generalized Assignment problem (GAP), so it becomes natural to solve SUM by using the algorithms developed for the GAP. The *Generalized Assignment Problem* is well studied in the literature and there have already been developed many approximation algorithms which guarantee different degrees of approximation on the solution. In fact, since the GAP is **NP**-Complete it is in general impossible to find an optimal solution in a polynomial time, therefore it becomes necessary to create algorithms that can find a non-optimal solution but still good enough. Here we show how we implemented the approximation algorithm described in [5] that, combined with another algorithm in [10], is provably a $(2+\epsilon)$-Approximation Greedy Algorithm.

An algorithm is an $\alpha$-approximation algorithm if $|OPT| \leq \alpha \cdot |ALG|$ for $\alpha \geq 1$, where $|ALG|$ is the value of the objective function for the feasible solution returned by the approximation algorithm, and $|OPT|$ is the value of the objective function for the optimal solution[5].

### ($\alpha$+1)-Approximation Algorithm for GAP

We chose to implement the algorithm described in [5] since it is one of the latest work about GAP, and since it is one of the best and easiest to implement approximation algorithm developed for this problem. In the paper [5] the authors state that using any $\alpha$-approximation algorithm for the knapsack problem, it is possible to construct an ($\alpha$+1)-approximation algorithm for the Generalized Assignment Problem in a greedy manner, using the concept of "residual profits" to assign items to bins.

The main idea of the algorithm is to solve many times the knapsack problem each time identifying one of the bins of the GAP model as a knapsack, and identifying as items to insert into the knapsack all the items given in input to the Generalized Assignment Problem. During each iteration, the knapsack problem will use as absolute size for the items the size that each of them has for the current bin, and as absolute profit the residual profit. The residual profit $p_i^{RES}$ of an item $i$ for the bin $j$ is defined in this way: $p_i^{RES} = p_{ij}$ if item $i$ is not selected for any other bin, otherwise $p_i^{RES} = p_{ij} - p_{ik}$ if item $i$ is selected for bin $k$.

Formally we use a vector T to indicate the tentative schedule during the algorithm, so $T[i] = j$ means that the item $i$ is scheduled to bin $j$, instead $T[i] = -1$ means that item $i$ is not scheduled to any bin. The residual profit in iteration $j$ is denoted by $P_j^{RES}[i]$ and it holds $P_j^{RES}[i] = p_{ij}$ if item $i$ is not scheduled to any bin ($T[i] = -1$) and $P_j^{RES}[i] = p_{ij} - p_{ik}$ if item $i$ is scheduled on bin $k$ (i.e. $T[i] = k$). Using the terminology of the SUM model the knapsack problem that is solved at each round has these parameters:

- each *knapsack* is a *mission* $M_j$

[5]It is probably easier to understand the definition of $\alpha$-approximation algorithm if we consider $\alpha \leq 1$, then we have that the condition is: $\alpha \cdot |OPT| \leq |ALG| \leq |OPT|$.

- the *capacity* of the knapsack is the utility *demand* $d_j$ of the mission $M_j$
- the *items* to insert into the knapsack at each round are all the *sensors* of the network
- the *size* of each item is the *utility offer* that each sensor have for the mission $j$
- the *profit value* for each item is the *residual profit* defined above, which is a function of the *profit offered* $p_{ij}$ by each sensor to a mission.

The algorithm adapted to the terminology used by SUM is presented in Algorithm 5.

**Algorithm 5** ($\alpha$+1)-Approximation Algorithm for GAP

```
1: for each sensor S_i do
2:    T[i] = −1
3: end for
4: for each mission M_j do
5:    Call α-Approximation Alg. for Knapsack to find a solution to mission
      M_j using the residual profit function P_j^RES
6:    for each S_i scheduled by the α-Approximation Alg. to M_j do
7:       T[i] = j
8:    end for
9: end for
```

The complexity of the ($\alpha$+1)-Approximation Algorithm for GAP is in general $O(m \cdot f(n) + m \cdot n)$, where $n$ is the number of sensors, $m$ is the number of missions and $f(n)$ is the running time of the $\alpha$-Approximation Algorithm for the knapsack.

### $\alpha$-Approximation Algorithm for the Knapsack

From what written above it is clear the need of implementing also an efficient $\alpha$-Approximation Algorithm for the *Knapsack Problem*[6].

[6]Given a set of items, each with a *size* $w_i$ and a *value* $p_i$, and a knapsack with a given *capacity* $c$, we have to determine which items to insert in the knapsack so that the *total size* of the chosen items is less than or equal to the knapsack's *capacity* while maximizing the *total value* of the chosen items.

Our choice fell on one of the most famous approximation algorithm for this problem which first appeared in [10]. This algorithm is a $(1+\epsilon)$-approximation algorithm[7] for an arbitrary $\epsilon > 0$, and it is also an FPTAS[8] i.e. its time and space complexity grows polynomially with $n$ (number of items) and $1/\epsilon$, in particular both space and time complexity are $O(n/\epsilon^2)$.

The Ibarra and Kim algorithm is a dynamic programming algorithm, and it is based on the profit values of the items. It defines the elements of a matrix A with $n$ rows (one for each item) and $|ALG|$ columns[9] (one for each possible value of the objective function). Since the value of $|ALG|$ is unknown (indeed it is the one that we want to compute with the algorithm), the matrix A is defined on $U$ column, where $U$ is any upper bound on the value of the optimal solution.

In particular, for $l = 1, \ldots, n$ and $v = 1, \ldots, U$ the element $A[l, v]$ represents the minimum capacity required to obtain a value of the objective function at least equals to $v$ using only the first $l$ items. If it is impossible to get $v$ as value of the objective function using only the first $l$ items then the rule is to set $A[l, v] = +\infty$. Formally:

$$A[l, v] = \min\{q : \sum_{i=1}^{l} p_i x_i \geq v, \sum_{i=1}^{l} w_i x_i \leq 1, x_i \in \{0, 1\}, i = 1, \ldots, l\}$$

Once defined all the elements of the matrix $A$, the value of the optimal solution is:

$$|ALG| := \max\{v : A[n, v] \leq c\}$$

The entire Ibarra-Kim algorithm is shown in Algorithm 6.

Since this FPTAS requires that each profit value is an integer number, and since we also have that the time complexity depends strongly by the maximum item profit, then we need to to use scaled integer profits different from original item profits. Formally stated, we will use $p'_i = \lfloor p_i/\delta \rfloor$ for $i = 1, \ldots, n$ , where $\delta$ depends from the required approximation error $\epsilon$ in the returned solution[10].

[7] So if we set $\alpha = (1 + \epsilon)$ it can be considered an $\alpha$-approximation algorithm.
[8] Fully Polynomial Time Approximation Scheme.
[9] $|ALG|$ is the value of the objective function for the approximated solution.
[10] $\delta := \frac{\epsilon \tilde{p}}{n}$, where $\tilde{p} = \max_i\{p_i\}$

**Algorithm 6** FPTAS for the knapsack problem

1: **for** $v = 1, \ldots, p'_1$ **do**
2: $A[1, v] := w_1$
3: **end for**
4: **for** $v = p'_1 + 1, \ldots, U$ **do**
5: $A[1, v] := +\infty$
6: **end for**
7: **for** $l = 2, \ldots, n$ **do**
8: **for** $v = 1, \ldots, p'_l$ **do**
9: $A[l, v] := \min\{A[l-1, v], w_l\}$
10: **end for**
11: **for** $v = p'_l + 1, \ldots, U$ **do**
12: $A[l, v] := \min\{A[l-1, v], A[l-1, v-p'_l] + w_l\}$
13: **end for**
14: **end for**

Finally to find the real value of the objective function we will have to backtrack which items are chosen to be inserted into the knapsack and then we will use the not-scaled profits to compute the original value of the objective function. So it is easy to understand that, as in all the dynamic programming algorithms, we also need to keep another matrix of pointers, that will allow us to backtrack the solution, i.e. to understand which items where inserted in the knapsack. This matrix of pointers will have the same dimensions of the matrix $A$ used to compute the optimal value of the objective function.

### Improvements of GAP and Knapsack algorithms

So finally we combined the GAP and Knapsack algorithms (as explained in Algorithm 5) to solve the SUM problem, and at the same time we modified them with three major improvements.

Implementing the two algorithms without any particular expedient, highlighted that there were problems related to the *memory usage* and also to the *effective time* spent to compute the solution.

As a matter of fact the Knapsack algorithm requires a lot of memory since it generates two matrices (one to compute the objective function and the other

to backtrack the solution) of dimension $n \times U$, where both $n$ and $U$ are very large. The number of items $n$ is the number of sensors that we generate and in our experiments this is a very large number since we want to be able to deal with very big sensor networks (thousands of them). Also the upper bound $U$ is really large since in the classic implementation of the Knapsack algorithm this upper bound is computed in this way: $U := \tilde{p} \cdot n$; such an upper bound is really not good, especially if we give in input to the knapsack algorithm a large number of items and the knapsack has a very low capacity (that is exactly the case of the SUM, since missions requires in average a utility that is reached by assigning three or at most four sensors to the mission). The fact that the dimensions of the matrices are very large, has also strong consequences on the effective computational time of the Knapsack algorithm, since it will have to fill a very big matrix to find the solution.

We solved the problem of *memory usage* and of *computational time* using three expedients that are described in the following paragraphs.

The **first expedient** is to reduce the number of items $n$ given in input at each round of the GAP algorithm to the Knapsack subroutine. Indeed we will delete from the input items the ones that have a zero profit for that specific bin $j$, and also the ones that are too big to fit into the bin (i.e. in terms of the SUM problem $e_{ij} > d_j$, and instead in terms of the Knapsack problem $w_i > c$). In this way we obtain a remarkable reduction of $n$, that in our specific test cases will be from thousands to tens of sensors; so the rows of the two matrices created by the Knapsack subroutine are drastically reduced.

The **second expedient** was taken to reduce the number of columns of the matrices used in the Knapsack subroutine, that is $U$. Our improvement here can be described in two step:

1. We solve the knapsack problem using the FPTAS with $U = \sum_i p_i$ and without creating the matrix of pointers. Finally we will find the value of $|ALG|$ (the optimal value of the objective function), as described above in Section 2.4.3. This computation will require much less memory space, since we use a better upper bound and also since we don't create the

matrix of pointers.

2. Now we run again the Knapsack subroutine but with $U = |ALG|$ and this time we generate also the matrix of pointers to keep track of which items are inserted into the knapsack. So the algorithms will generate two matrices with the minimum number of columns, thus saving a lot of memory space.

The first and second expedients improve both memory usage and effective computational time, since they reduce the dimensions of the matrix that is used to solve the problem. Simply stated they limit the search space by reducing the number of possible states.

The **third expedient** improves the memory usage but not the effective time spent to compute the solution in the Knapsack subroutine. It consists in substituting the $n \times U$ matrix used to compute the value of the objective function with a $2 \times U$ matrix (but the matrix of pointers remains always a $n \times U$ matrix). This idea derives from the dynamic programming implementation of the knapsack algorithm (Algorithm 6), that requires only the value contained in the previous row $l - 1$ to compute the value of a row $l$. Making use of this observation we can generate only a $2 \times U$ matrix, and we can compute the value of the cells of a row by keeping only the previous row and overwriting with the new computed values the current row (that possibly contains older values no more required).

In conclusion the interesting thing is that using the GAP $(\alpha+1)$-approximation algorithm to solve the SUM, which calls as a subroutine the Knapsack $\alpha$-approximation algorithm described above (where $\alpha = 1 + \epsilon$), produces a **$(2+\epsilon)$-approximation algorithm** for the Sensor Utility Maximization problem where $\epsilon > 0$ is the max error that we want in the returned solution.

As it is stated in [5] the time complexity of this algorithm will be a function of the time complexity of the Knapsack $\alpha$-approximation algorithm used[11], and in particular it will be $O\left(\frac{mn}{\epsilon^2}\right)$ where $m$ is the number of missions and $n$ is the number of sensors.

[11] That is $O\left(\frac{n}{\epsilon^2}\right)$, as we already stated.

Finally we observe that, in theory, this is the best possible algorithm to solve SUM, from both the point of view of approximation guarantee and time complexity.

## 2.5 Performances

To evaluate the performances of all the different algorithms that we presented we will use a Java simulator developed in [8]. In the same way we will assume that all sensors know their geographical locations.

Each mission has a maximum demand ($d_j$), which is the maximum amount of sensing resources that a mission might require, and a profit ($p_j$), which represent the importance of the mission (the higher the profit the more important). The utility offer ($e_{ij}$) of a sensor to a mission is a function of the geographical distance between them: the closer the sensor to the mission, the higher its utility. The utility is 1 if the sensor and the mission lie at the same location.

So it follows that, in the same way, the profit offer ($p_{ij}$) of a sensor to a mission will be a function of the distance of the sensor from the mission, but this value will also be scaled by the profit of the mission considered. In fact it holds that $p_{ij} = e_{ij}/d_j \cdot p_{ij}$.

### 2.5.1 Assumptions

Here we summarize the assumptions that we considered:

- Nodes are deployed in uniformly random locations in a $400m \times 400m$ field. When nodes are deployed we ensure that the network is connected.
- Missions are created in uniformly random locations in the field.
- A base station is located in the center of the left edge of the battlefield (that is rectangular).
- Each mission has an exponentially distributed demand $d_j$, so there will be many missions with low demand and few missions with high demand

but where the average value of the demand is 2. However, we cap the demand to a maximum of 6 in order to limit the number of missions with a too high demand.

- Associated with each mission there is also an exponentially distributed profit $p_j$, and here the average value is 1. As in the case of the utility demand, this simulates realistic scenarios in which many missions have a low priority and few missions are really critical missions.

- The utility of a sensor $S_i$ to a mission $M_j$ will be:

$$e_{ij} = \begin{cases} \frac{1}{1+D_{ij}^2/c} & \text{if } D_{ij} \leq SR \\ 0 & \text{otherwise} \end{cases}$$

  where $D_{ij}$ is the distance between $S_i$ and $M_j$, and $SR$ is the global sensing range. This means that when a sensor have the same location of a mission then the utility offer is equal to 1, and it models realistic signal attenuation which is relative to the square of the distance from a source. When the mission is outside of a sensor's sensing range the utility is 0. In our experiments $c = 60$ and $SR = 30m$.

- Each sensor can only be assigned to a single mission, and so once assigned the full utility of the sensor is allocated to support the mission requirement.

- For communication, we assume perfect channels with no errors or collisions. Hence each message is only sent once and it is guaranteed to be delivered.

- We do not care about the number of messages that have to be exchanged between sensors and base station to apply the algorithms and then to configure the network. Indeed in this work we are not looking for the best algorithm in terms of the one with the less communication overhead.

### 2.5.2 Experimental Setup

In these experiments we assume prior knowledge about all missions, and like in [8] we perform three different experiments in which the field size ($400m \times 400m$) is kept constant, but the density of the nodes (i.e. number of sensors in the network) in the field and the number of missions are varied. The number of sensors in the network is different for each experiment: 200 for the first, then 500, and finally 1000 sensors. For each node density, we vary the number of missions from 10 to 100, with an increment of 10 at each step.

In the following results we show the average of 10 runs for the *Total Network Profit* achieved by the solution, which is the sum of all the profits $p_{ij}$ that sensors have for missions to which they are assigned[12]. Our goal is to maximize this value.

### 2.5.3 Simulation Results

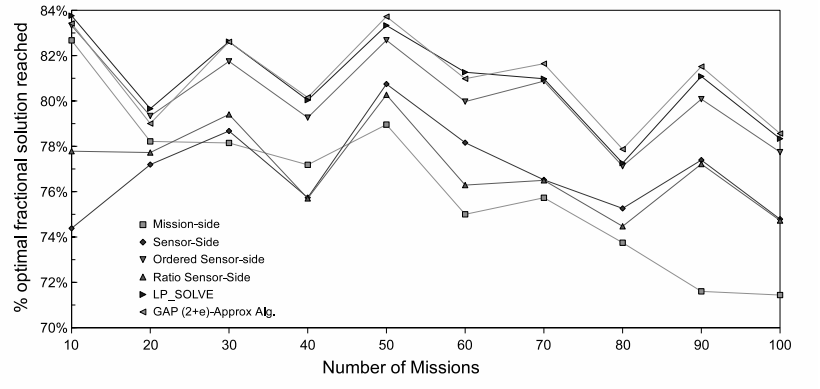
The Total Network Profit achieved by each different algorithm is compared to the one achieved by the *optimal fractional solution*, which is the solution to the relaxed linear programming formulation of SUM. By relaxed formulation we mean a linear programming formulation of SUM where $x_{ij}$ is not anymore integer but it becomes real valued, i.e. now we have $x_{ij} \in [0, 1]$ (and not anymore $x_{ij} \in \{0, 1\}$). In this solution a sensor could be assigned to more than one mission, since we could assign each fraction of its utility to different missions.

The Total Network Profit achieved by the optimal fractional solution is computed using *LP_SOLVE* as a classic linear programming solver and not anymore as an Integer Linear Programming solver.

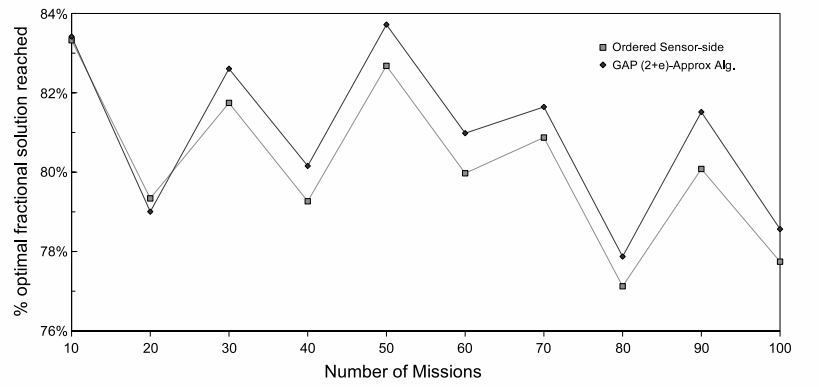
In the first set of results (shown in Fig. 2.2), we show the total network profit achieved by the different algorithms as a percentage of the total network profit achieved by the optimal fractional solution, with a network of 200 sensors. Note that the optimal fractional solution is not always a strict upper bound on our results, in fact the *integrality gap*[13] between the relaxed

[12] In other words it is again the value of the objective function $\sum_i \sum_j p_{ij} x_{ij}$.

[13] If the relaxed solution to an Integer Linear Programming is indicated as $|LPR|$ and the




(a) All algorithms (200 sensors)

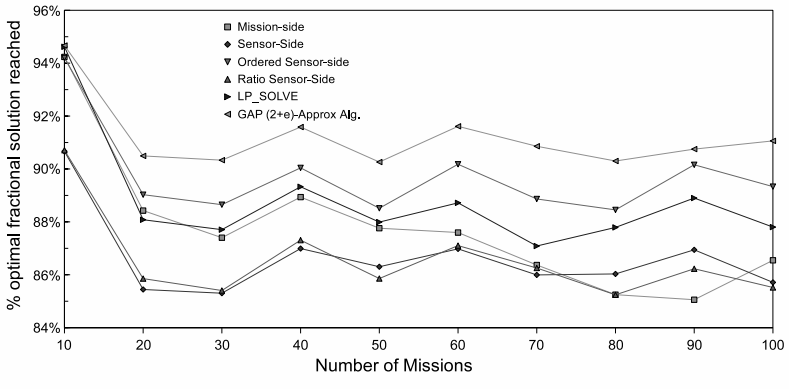



(b) Ordered Sensor-side and (2+$\epsilon$)-approximation algorithms (200 sensors)

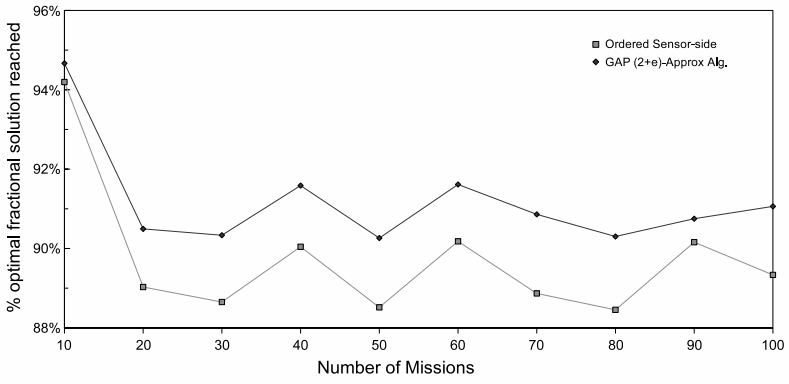
Figure 2.2: (200 sensors) Percentage of the optimal fractional solution vs missions.

LP problem and the ILP problem could be very high. With this in mind, we see in Figure 2.2a that the $(2+\epsilon)$-approximation algorithm, $LP\_SOLVE$ and the Ordered Sensor-side approach are the best solutions to this instance of the SUM. Since we are using a small number of sensors $LP\_SOLVE$ often manages to find a really good solution to the problem, but what is relevant is that both Ordered Sensor-side and (2+$\epsilon$)-approximation algorithms have performances comparable to $LP\_SOLVE$. In Fig. 2.2b we consider only the Ordered Sensor-side and (2+$\epsilon$)-approximation algorithm and we notice that

integer solution is $|ILP|$ then: *Integrality Gap* $= \frac{|LPR|}{|ILP|}$




(a) All algorithms (500 sensors)




(b) Ordered Sensor-side and (2+$\epsilon$)-approximation algorithms (500 sensors)

Figure 2.3: (500 sensors) Percentage of the optimal fractional solution vs missions.

the difference between the two solutions is 0.5%-1% in average, which means that they have more or less the same performances in terms of goodness of the solution.

From Figure 2.3 and 2.4 we note that $LP\_SOLVE$ performances (compared to the Ordered Sensor-side and the (2+$\epsilon$)-approximation algorithm performances) decrease with the increment of the number of sensors, in fact with 1000 sensors (Fig. 2.4) the gap between the (2+$\epsilon$)-approximation algorithm and $LP\_SOLVE$ is around 3%. The same thing happens with the Ordered Sensor-side algorithm which has increasing lower performances compared to (2+$\epsilon$)-approximation algorithm, this is clearly shown in Fig. 2.3b and 2.4b.

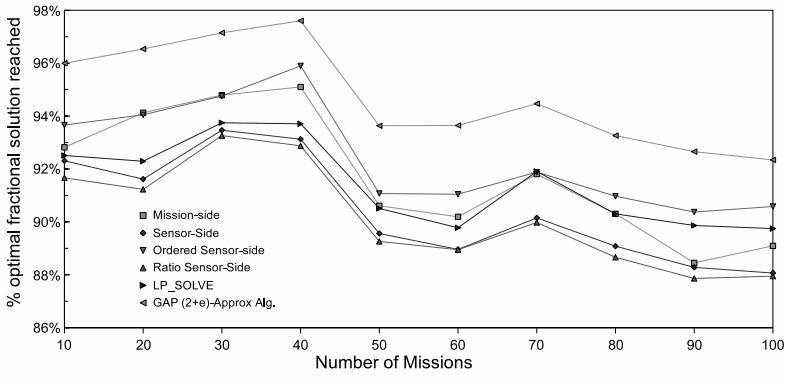
Anyway the gap between $LP\_SOLVE$ and (2+$\epsilon$)-approximation algorithm is greater than the gap between Ordered Sensor-side and (2+$\epsilon$)-approximation algorithm (which is around 1.5%).

Despite the general degrade of the performances of the other approaches compared to the (2+$\epsilon$)-approximation algorithm while increasing the number of sensors, we observe a general improvement on the percentage of the optimal fractional solution achieved by all the algorithms. This is shown in Figure 2.4b where the maximum percentage of the optimal fractional solution achieved by the (2+$\epsilon$)-approximation algorithm is around 98%, while instead with 200 sensors in Fig. 2.2b was around 84%.

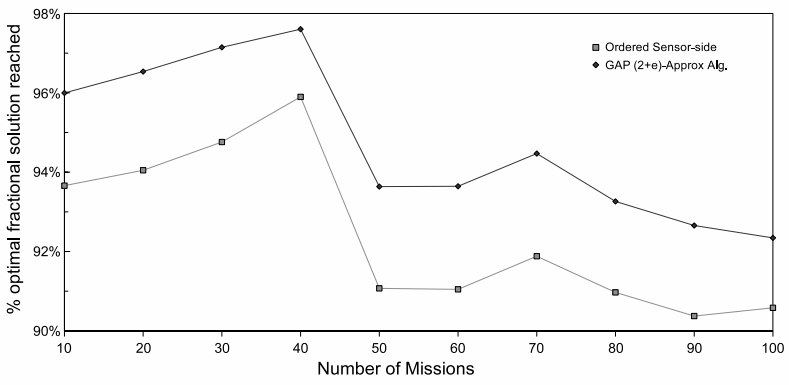
Concentrating for example on Figure 2.4a (but we could also look at Fig. 2.2a and fig:500:a) we notice that keeping constant the number of sensors while increasing the number of missions leads to a global degradation of the performances. Indeed, the percentage of optimal fractional solution achieved by the (2+$\epsilon$)-approximation algorithm with 10 missions is around 96%, but instead while dealing with 100 missions the performances decrease to 92%.

In conclusion, we infer from these results that the best algorithm to solve the SUM with a very good degree of approximation is the (2+$\epsilon$)-approximation algorithm described in Section 2.4.3, thought this is not the best in terms of effective time spent to compute the solution and also of memory usage (even if we strongly improved both). The time complexity of this algorithm is $O\left(\frac{mn}{\epsilon}\right)$, so if we require an high precision in the solution found (i.e. a very small $\epsilon$) we will have a very big multiplicative constant (that is $1/\epsilon^2$), and this is why other algorithms with a worse time complexity go faster in real case scenarios.

For all these reasons we believe that the *Ordered Sensor-side algorithm* is a good compromise between optimality of the solution found and time and space complexity performances. In fact, we noticed that the effective time spent by this algorithm is much less than the time of the (2+$\epsilon$)-approximation algorithm, and also that there is not a big use of the memory to compute the solution.




(a) All algorithms (1000 sensors)




(b) Ordered Sensor-side and (2+$\epsilon$)-approximation algorithms (1000 sensors)

Figure 2.4: (1000 sensors) Percentage of the optimal fractional vs missions.

## 2.6 Conclusion and Future Work

In this Chapter, we defined the Sensor Utility Maximization (SUM) problem, were the goal is to maximize the total network profit, i.e. to find an assignment of sensors to missions that maximizes the total benefit for the sensor network by sending the utility where it is most helpful. We described the differences and similarities with other similar problems in the literature, and in particular we compared it to the Sensor Matching with Demands (SMD) problem. We analyzed its complexity, showing that is NP-Complete and that it is equivalent to the Generalized Assignment Problem (GAP). Furthermore we looked at several centralized algorithms to solve it, applying also some techniques al-

ready known for the Generalized Assignment Problem. Our simulation results show that one of our greedy algorithm, called Ordered Sensor-side greedy, has performances comparable to the state-of-the-art algorithms developed to solve GAP.

The challenge now could consist in the development of distributed algorithms to solve SUM, and also to compare the performances of these distributed approaches with the centralized solutions described in this Chapter.

A very interesting future work could be to modify the SUM model to include also the concept of effective cost of sensors and budget of missions, maybe creating a new model that could be seen as the fusion between SUM and SMD.

Finally, in this paper we assumed that sensor utilities to a mission are additive. This is not always the case for every scenario, so we could find a way to modify the SUM model with some side constraints in such a way to cover also the scenarios in which this is not true.

# Conclusion

The two projects presented in this thesis can be considered a very relevant contribution to the branch of the International Technology Alliance project (ITA) which deals with sensor networks. Both sensor deployment and sensor assignment problems were modeled with a kind of knapsack-style approach, which is the most innovative contribution to ITA. In this way we showed that techniques developed to solve knapsack problems can be applied in this field to decide how to deploy and configure military sensor networks.

Indeed, in Chapter 1, we subdivided the sensor deployment problem into two main subproblems: sensor assignment to zones and sensor deployment inside each zone. The first subproblem was modeled as an extension of the multiple knapsack problem, by including some additional information on sensors and zones inside the model, and it had been solved using a classic Constraint Satisfaction Problem solver (even if we could have also used an Integer Linear Programming solver). For the second part, instead, we developed a very simple algorithm to automatically deploy sensors assigned to a particular zone.

An interesting approach to solve the extended multiple knapsack model could have been to develop greedy and approximation algorithms, based on the ones already developed in the literature to solve multiple knapsack style problems. But as a matter of fact in Chapter 2 we implemented a very famous approximation algorithm to solve the Generalized Assignment Problem (GAP), and since multiple knapsack is a particular case of GAP we could have used a similar approach.

Anyway in our experiments we showed that our solution works quite well for medium sized instances of the problem, but on the other hand it performs

very badly for big instances since we are using a common CSP solver. The issue of the time spent is easily solvable by developing an approximation greedy algorithm for this problem and using this instead of a CSP solver.

Interesting was also the simulation system architecture that we designed and implemented. We showed that implementing the problem solver as a webservice makes the system components very independent, so that they are completely interchangeable. Furthermore we instrumented the game Battlefield 2, with the aim of using it as a simulation environment in which sensors are deployed using the output of the problem solver. This kind of gaming virtual environment is often used by US and UK armies to train their soldiers to improve mission accomplishing strategies; thus in this way our solver could be really used in the train stage by the commanders. Finally, thanks to the system architecture the solver could be used also in real world, by substituting the game server with a real world central station (where decisions to deploy real sensors are usually taken).

In Chapter 2 we discussed the problem of the sensor assignment to competing missions. This problem differs from the previous one because we now have to configure an already deployed sensor network and we are using sensors of the same type (i.e. no multimodal sensors). The interesting fact is that also this problem was modeled with a knapsack approach, taking inspiration from the sensor deployment problem already modeled as an extension of the multiple knapsack.

We formally proved that the sensor assignment problem is equivalent to the Generalized Assignment Problem (GAP) which is very well studied in the literature. So instead of using a Constraint Satisfaction Problem solver or an Integer Linear Programming solver to solve it, we focused on the development of new greedy approximation algorithms based on some already developed GAP algorithms. In particular we showed that the best solution to this NP-complete problem is given by a version of the very famous $(2+\epsilon)$-approximation algorithm described in [10] which we improved with some expedient. Anyway we also showed that we developed a new greedy approximation algorithm, called Ordered Sensor-side greedy, which returns a solution that is almost as good

as the one returned by the (2+$\epsilon$)-approximation algorithm. Furthermore we observed that Ordered Sensor-side greedy has a running time and a memory usage that are often better than the ones of the improved (2+$\epsilon$)-approximation algorithm.

Finally, it is reasonable to think that in the real world these two problems could arise one after the other. A typical scenario in which this could happen is when there is no sensor network deployed on the battlefield, and so we have to deploy sensors by maximizing the coverage area and by satisfying all the mission information requirements. When the sensor network will be deployed in the battlefield there could be many missions competing for the same sensor resource, so in this case we have to solve the problem of assigning sensors to competing missions. In this scenario the assumption is that all the sensors are of the same type (i.e. there are no multimodal sensors), since the sensor assignment model was designed only to deal with such sensors.

In conclusion, we believe that this thesis gives a very useful contribution to the field of military sensor networks. First of all because this is the first time that somebody deals with very big sensor networks, but also because of the new problems defined and the new solutions developed to solve them.

# Appendix A

# Sensor Deployment - User Manual

This manual documents how to run the system described in Chapter 1 – it should be helpful to a commander who wants to know which are the best positions where to place sensors, given a set of available sensors and of selected zones of a map.

**Note**: This manual assumes that you have already installed the system correctly, if you didn't please see the Maintenance Manual (Appendix B) and follow the Installation Instructions.

## A.1 Starting the system

There are three main components which require to be executed at the same time - the webservice, the Battlefield 2 mod server and the Commander's Interface.

The webservice can be executed by simply starting the Apache tomcat service, that under WindowsXP can be done by selecting "Start→Configure Tomcat" and then by pushing the "Start" button. This will automatically start also the Axis Platform that is located inside Apache Tomcat (after a proper installation of the system), and so it will also start the webservice

called "DeploySensorsService".

The Battlefield 2 mod server can be executed by browsing to the folder "Battlefield2/ServerConfig" and then executing the file "bf2server.exe". Note that before executing the server, it has to be configured with the correct IP, as specified in the README file inside the installation folder "Software/Battlefield 2 Mod".

The Commander Interface can be simply executed by browsing into its folder and then by clicking on the file "ComInterface.bat" if you are in a WindowsXP environment. If you are not under WindowsXP you have to open a command prompt, browse to the folder "CommanderInterface" and then type:

```
java -jar ComInterface.jar
```

Finally all the BF2 players that wants to use this infrastructure can start their game client modified with the Mod that is supposed to be correctly installed in their machine. To start the game mod installed in a client machine you just need to browse to the folder of the game "Battlefield2" and then click on "RunBF2Client Debug.bat" or on "RunBF2Client Release.bat", depending if you want to run the game in debug[1] or in release[2]. Note that before allowing the first player to connect to the BF2 server you should be sure to have stored the deployment of the sensors through the Commander Interface.

## A.2 Using the system

Let's take a look at the typical sequence of operations in such a system:

1. Start the webservice, the BF2 mod server and the commander interface.

2. Use the commander interface to create sensors and select zones and then wait for the answer of the webservice, that will solve the problem (if

[1] that means in a window at a lower resolution, with the possibility to see debug/error messages

[2] that means at higher resolution on full screen

there is a solution). At the same time, the WebService will store the sensor deployment into a static variable.

3. The players can now start their client of the game with the "Mod" installed and then connect to the server "PlanAndPlay Test Server"

4. When the first player will connect to the BF2 server, this will ask to the webservice for the stored sensor deployment (previously set by the commander interface).

### A.2.1 Using the Commander's Interface

When first executing the commander's interface you will be prompted to input the URL of the webservice. If it is in the same machine where you are running the Commander's Interface, then you will have only to write "local", as you can see in Figure A.1.

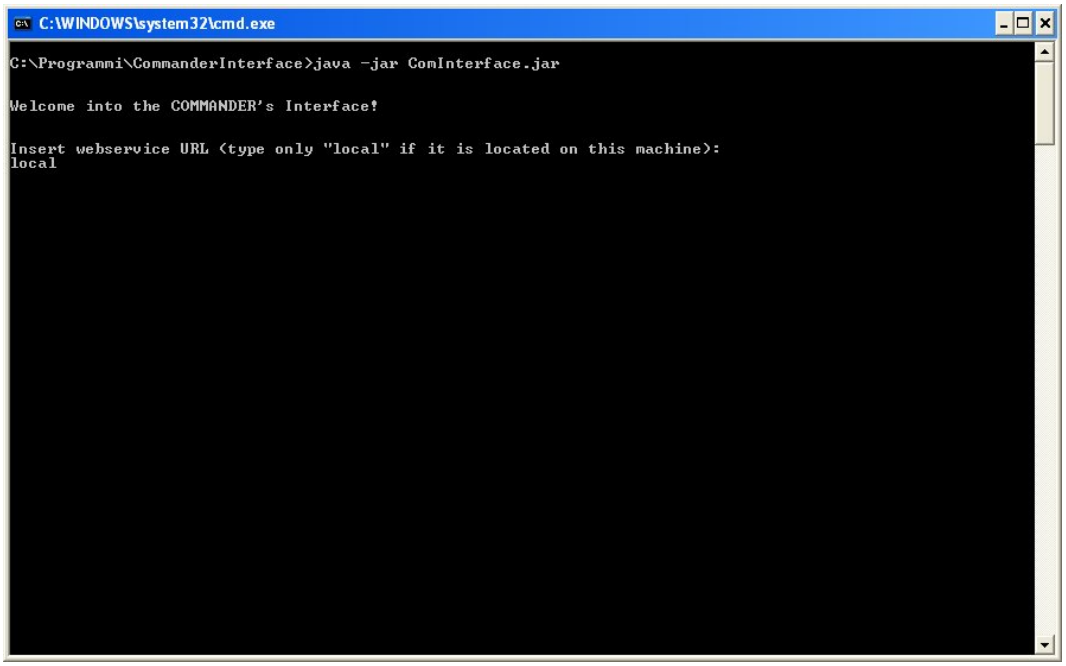

C:\WINDOWS\system32\cmd.exe
C:\Programmi\CommanderInterface>java -jar ComInterface.jar
Welcome into the COMMANDER's Interface!
Insert webservice URL (type only "local" if it is located on this machine):
local

Figure A.1: Locating webservice.

Then you will see a list of commands with a little description of what they will do. The most important between these commands is "new", which actually allows the commander to set the parameters such as sensors and zones and then to send this parameters to the webservice that will solve the problem and will store the solution. Let's analyze each step of the "new" command:

1. You can see in Figure A.2, that the deployment will be done on the map "PlainMap" and it says also which is the extension of the map. It asks to insert the side of zone that you want to use.

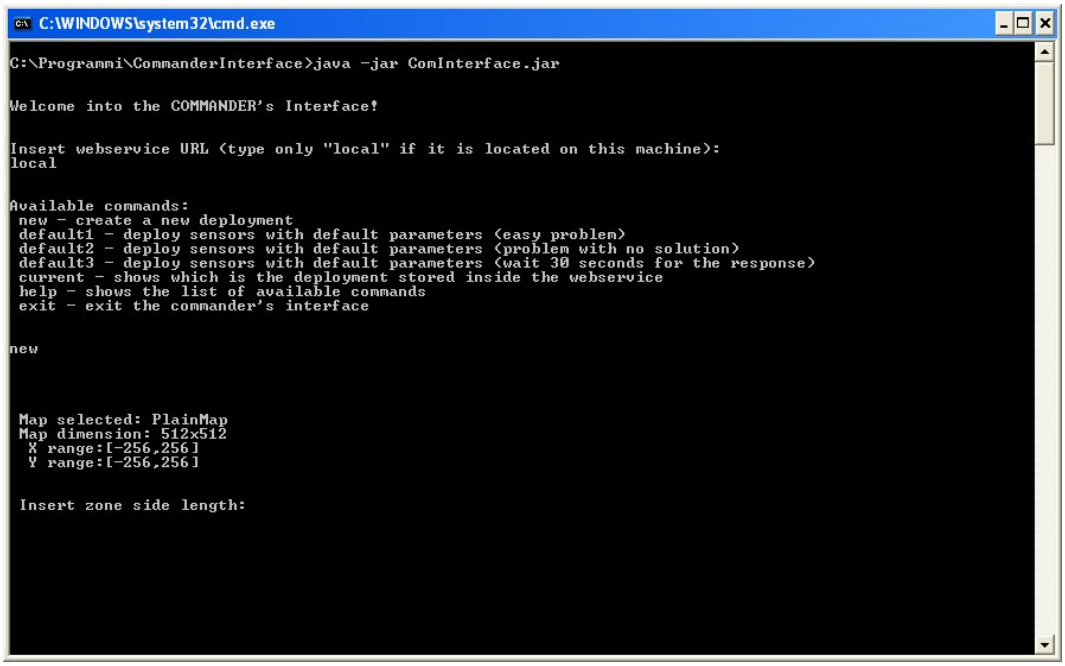

C:\WINDOWS\system32\cmd.exe
C:\Programmi\CommanderInterface>java -jar ComInterface.jar
Welcome into the COMMANDER's Interface!
Insert webservice URL (type only "local" if it is located on this machine):
local
Available commands:
new - create a new deployment
default1 - deploy sensors with default parameters (easy problem)
default2 - deploy sensors with default parameters (problem with no solution)
default3 - deploy sensors with default parameters (wait 30 seconds for the response)
current - shows which is the deployment stored inside the webservice
help - shows the list of available commands
exit - exit the commander's interface
new
Map selected: PlainMap
Map dimension: 512x512
X range:[-256,256]
Y range:[-256,256]
Insert zone side length:

Figure A.2: Inserting zone side.

2. Once you inserted the side it will write, as in Figure A.3, that the system will use a different number since the system will actually solve a simplified version of the problem that you are setting up.

3. Now it asks you how many zones you want to select, as shown in Figure A.4 and it goes through the details of each zone that you will select, like in Figure A.5.

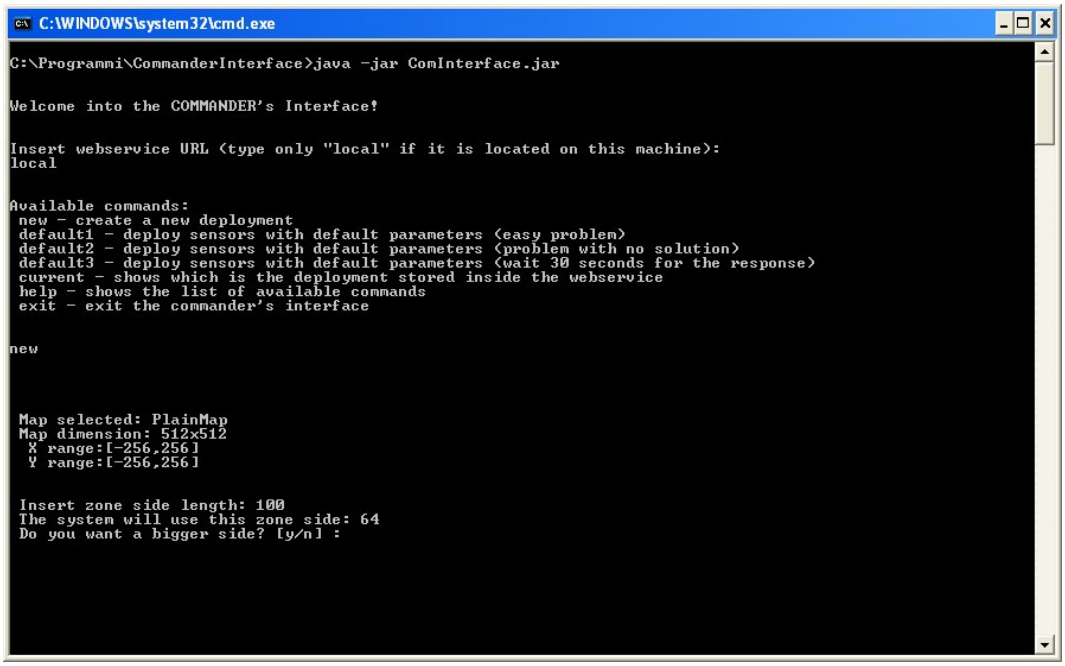

C:\WINDOWS\system32\cmd.exe
C:\Programmi\CommanderInterface>java -jar ComInterface.jar
Welcome into the COMMANDER's Interface!
Insert webservice URL (type only "local" if it is located on this machine):
local
Available commands:
new - create a new deployment
default1 - deploy sensors with default parameters (easy problem)
default2 - deploy sensors with default parameters (problem with no solution)
default3 - deploy sensors with default parameters (wait 30 seconds for the response)
current - shows which is the deployment stored inside the webservice
help - shows the list of available commands
exit - exit the commander's interface
new
Map selected: PlainMap
Map dimension: 512x512
X range:[-256,256]
Y range:[-256,256]
Insert zone side length: 100
The system will use this zone side: 64
Do you want a bigger side? [y/n] :

Figure A.3: The side used by the system.

4. Then it asks how many sensors are available and it lets you define all the parameters for each sensor, as shown in Figure A.6.

5. Finally it sends the parameters to the webservice and it waits for the solution, that will be in the format shown in Figure A.7.

Finally the players can now connect to the Battlefield 2 "Plan And Play Test Server" and there will have invisible sensors deployed inside the map. The player knows when he is accessing or exiting a certain sensor area since on the screen of the player inside the game it will appear a message, as shown in Figure A.8.

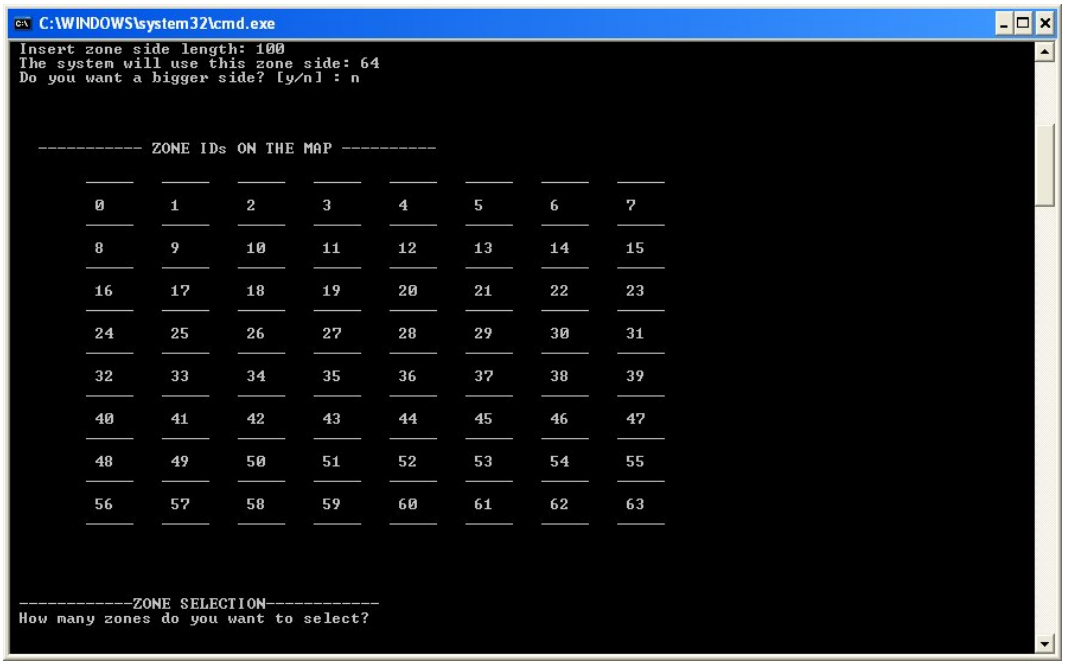

C:\WINDOWS\system32\cmd.exe
Insert zone side length: 100
The system will use this zone side: 64
Do you want a bigger side? [y/n] : n
---------- ZONE IDs ON THE MAP ----------
0 1 2 3 4 5 6 7
8 9 10 11 12 13 14 15
16 17 18 19 20 21 22 23
24 25 26 27 28 29 30 31
32 33 34 35 36 37 38 39
40 41 42 43 44 45 46 47
48 49 50 51 52 53 54 55
56 57 58 59 60 61 62 63
------------ZONE SELECTION------------
How many zones do you want to select?

Figure A.4: Selecting zones.

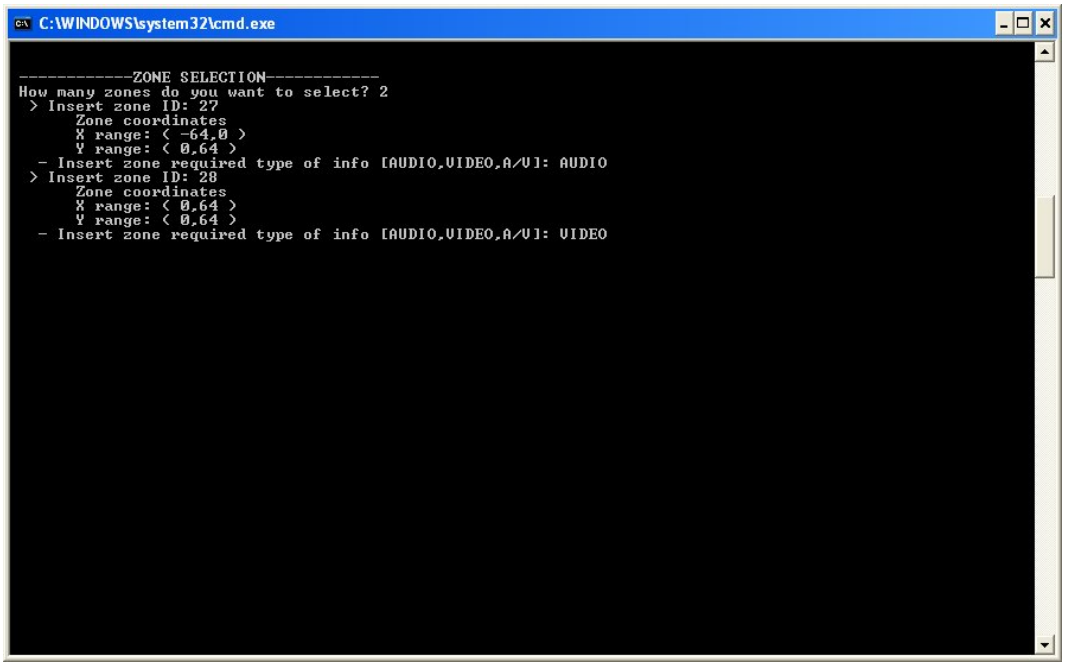

C:\WINDOWS\system32\cmd.exe
------------ZONE SELECTION------------
How many zones do you want to select? 2
> Insert zone ID: 27
Zone coordinates
X range: ( -64,0 )
Y range: ( 0,64 )
- Insert zone required type of info [AUDIO,VIDEO,A/V]: AUDIO
> Insert zone ID: 28
Zone coordinates
X range: ( 0,64 )
Y range: ( 0,64 )
- Insert zone required type of info [AUDIO,VIDEO,A/V]: VIDEO

Figure A.5: Creating zones.

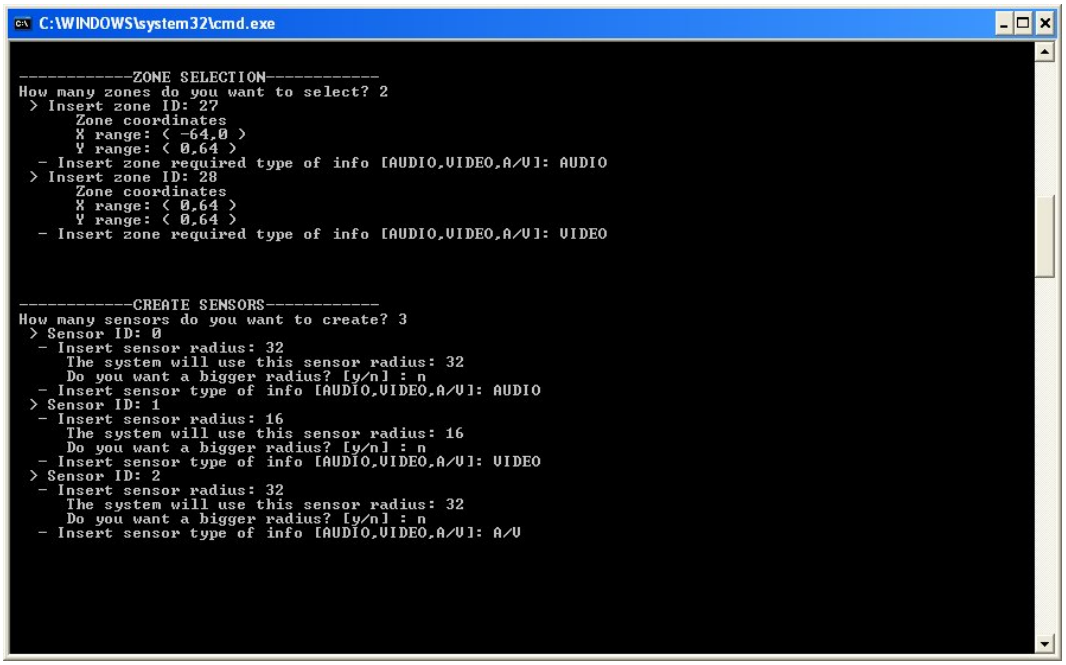

C:\WINDOWS\system32\cmd.exe
----------ZONE SELECTION----------
How many zones do you want to select? 2
> Insert zone ID: 27
Zone coordinates
X range: ( -64,0 )
Y range: ( 0,64 )
- Insert zone required type of info [AUDIO,VIDEO,A/V]: AUDIO
> Insert zone ID: 28
Zone coordinates
X range: ( 0,64 )
Y range: ( 0,64 )
- Insert zone required type of info [AUDIO,VIDEO,A/V]: VIDEO
----------CREATE SENSORS----------
How many sensors do you want to create? 3
> Sensor ID: 0
- Insert sensor radius: 32
The system will use this sensor radius: 32
Do you want a bigger radius? [y/n] : n
- Insert sensor type of info [AUDIO,VIDEO,A/V]: AUDIO
> Sensor ID: 1
- Insert sensor radius: 16
The system will use this sensor radius: 16
Do you want a bigger radius? [y/n] : n
- Insert sensor type of info [AUDIO,VIDEO,A/V]: VIDEO
> Sensor ID: 2
- Insert sensor radius: 32
The system will use this sensor radius: 32
Do you want a bigger radius? [y/n] : n
- Insert sensor type of info [AUDIO,VIDEO,A/V]: A/V

Figure A.6: Creating Sensors.

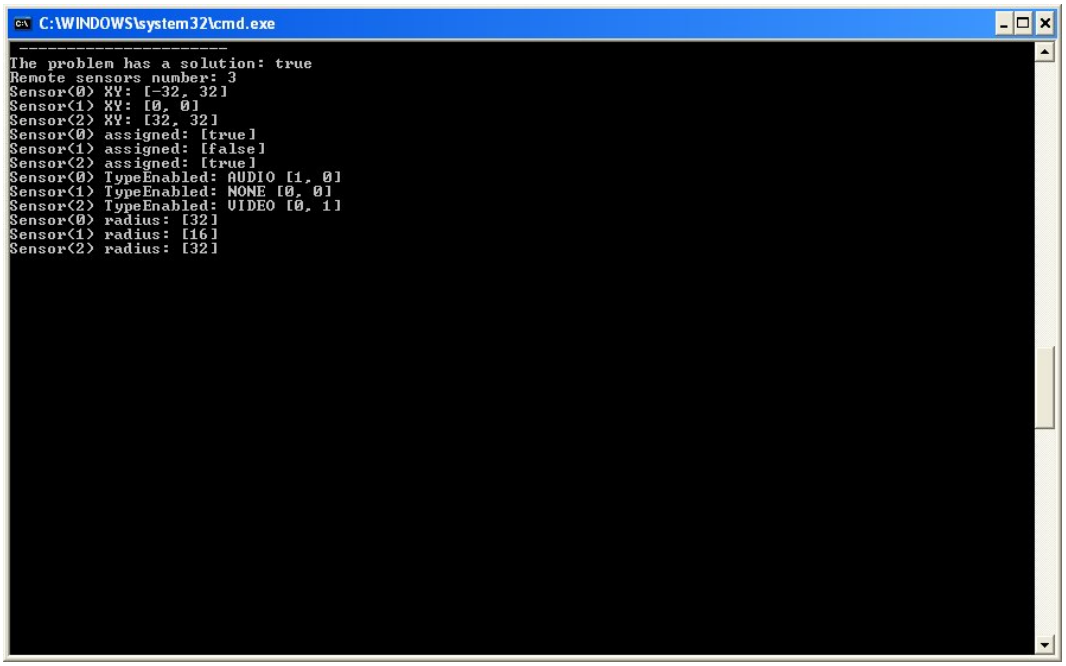



Figure A.7: Solution sent by the webservice.

Figure A.8: The message that appears entering a sensor area in BF2.

# Appendix B

# Sensor Deployment - Maintenance Manual

This manual concern the system described in Chapter 1. This brief manual should be helpful to people who want to install the program, modify the program, extend the program, or be aware of which are the known bugs. In this document we give also a brief description of each of the source files.

## B.1 Installation Instructions

The system is composed by three main component, that are actually three pieces of software, and each one could be considered as an independent application. Let's analyze the folder structure in the CD that contains the software and the source code:

- `Software` - which contains everything you have to install to run the system
- `src` - which contains the source code

The folder `Software` contains three directories, which reflect the system architecture:

- `CommanderInterface` - which contains the Interface for the commander

- `WebService` - which contains the platform where you have to insert the webservice, and the webservice itself

- `Battlefield 2 Mod` - which contains the plug-in developed for BF2 and other needed game patches

Each of these folders contains a README.TXT file that explains how to install each component. The Commander's interface can be installed on every OS since it is written in java and it is a jar file. The webservice is also written in java so it could be installed on every OS, but the installer for Apache tomcat included in the CD is only for WindowsXP, so if you want to install the webservice in a OS that is not WindowsXP you will have to download the proper version of Apache Tomcat. The BF2 "mod" (i.e. modified) game server is exclusively compiled for WindowsXP, so it has to be installed in a WindowsXP environment.

To check if the webservice is well installed you could start the Apache Tomcat service, and then you could open a browser and write the following URL:
"`http://localhost:8080/axis`" and then click on the link "List" and verify that "DeploySensorsService" is in the list.

Note that it is better to install all the three components on the same machine since this is the default configuration. You can also decide to install the Commander Interface in a different PC and leave the webservice and the BF2 mod game server on another machine; in this case you will have only to enter the proper URL of the webservice in the commander interface when it will require the address of the webservice. You could also decide to install all the three components on three different machines, but to do this you will have to change the code inside the file "Battlefield2/mods/PlanAndPlay/scoringCommon.py" and in particular inside the function "OnPlayerConnect(player)" and substitute the correct URL of the webservice in the line:

```
deploy = ServiceProxy("http://localhost:8080/axis/services
/DeploySensorsService?wsdl")
```

And finally you just need to save the file and to restart the game server.

## B.2 System Execution

There are three main components which require to be executed at the same time - the webservice, the Battlefield 2 modified game server and the Commander's Interface.

The webservice can be executed by simply starting the Apache tomcat service, that under WindowsXP can be done by selecting "Start→Configure Tomcat" and then by pushing the "Start" button. This will automatically start also the Axis Platform that is located inside Apache Tomcat (after a proper installation of the system), and so it will also start the webservice called "DeploySensorsService".

The Battlefield 2 mod game server can be executed by browsing to the folder "Battlefield2/ServerConfig" and then executing the file "bf2server.exe". Note that before executing the server, it has to be configured with the correct IP, as specified in the README file inside the installation folder "Software/Battlefield 2 Mod".

The Commander Interface can be simply executed by browsing into its folder and then by clicking on the file "ComInterface.bat" if you are in a WindowsXP environment. If you are not under WindowsXP you have to open a command prompt, browse to the folder "CommanderInterface" and then type:

```
java -jar ComInterface.jar
```

Finally all the BF2 players that wants to use this infrastructure can start their game client modified with the Mod that is supposed to be correctly installed in their machine, as specified in the README file in the folder "Software/Battlefield 2 Mod". To start the game mod installed in a client machine you just need to browse to the folder of the game "Battlefield2" and then click on "RunBF2Client Debug.bat" or on "RunBF2Client Release.bat", depending if you want to run the game in debug[1] or in release[2]. Note that before allowing the first player to connect to the BF2 server you should be sure to have stored the deployment of the sensors through the Commander Interface.

[1] that means in a window at a lower resolution, with the possibility to see debug/error messages

[2] that means at higher resolution on full screen

So, just to understand better the last sentence, let's see which is the typical sequence of operations in such a system:

1. Start the webservice, the BF2 mod server and the commander interface.

2. Use the commander interface to create sensors and select zones and then wait for the answer of the webservice, that will solve the problem (if there is a solution). At the same time, the WebService will store the sensor deployment into a static variable.

3. The players can now start their client of the game with the "Mod" installed and then connect to the server "PlanAndPlay Test Server" [3].

4. When the first player will connect to the BF2 server, this will ask to the webservice for the stored sensor deployment (previously set by the commander interface).

## B.3 Hardware and Software dependencies

This section summarizes the hardware and software dependencies of the entire system.

### B.3.1 Hardware dependencies

There are no particular hardware dependencies, except for Battlefield 2 on the client side. Indeed it is required a graphic card that has to be in the list of the graphic cards which are compatible with the game, this list is in the game requirements. Obviously also all the other requirements of the official game have to be respected.

Instead for the commander interface, the webservice and the BF2 server there are no particular hardware requirements.

[3] You will have noticed that somewhere we use the name "PlanAndPlay", this is because the "SensorDeployMod" developed for BF2 has adapted and expanded the code of the Mod developed by Daniele Masato in the project "Plan And Play".

### B.3.2 Software dependencies

**Java 1.6** Since the commander interface and the webservice are written in java they require the Java VM installed on the machines in which they will run. This is not included inside the CD, but you can download it from `http://java.sun.com`.

**Apache Tomcat 6.0.2** This is an application server that allows application written in Java to be executed on the server by a client. This software is included in the CD.

**Axis 1.4** This is a platform for developing and deploying webservices written in Java. It is itself a web application that has to be installed inside Tomcat. Also this software is included in the CD

**Battlefield 2 and Patches** The original Battlefield 2 game is for obvious reasons not included in the Installation CD. But the other patches that you will have to install are all attached.

**choco-1.2.03** This is a Java library that is used by the webservice to solve the problem of deploying the sensors inside the zones in an optimal way. This type of solver is called a CSP[4] solver, and so "choco" is a library to solve CSP's. This library is in included in the installation CD.

## B.4 Space and Memory requirements

Installing the Battlefield 2 server or client will require 2.3 GB of hard disk space, and this is the same also for the patches. Anyway if you will install the server, even if during the installation process they say that it is required to have 2.3 GB of free space, at the end of the day the space occupied by the server will be only 530 MB, already including the patches.

With regards to memory requirements, it is not recommended to run the Battlefield 2 server and the client on the same machine since if there is not

[4]Constraint Satisfaction Problem

enough memory the performances of the game could be compromised. Another important thing is that if the problem that the webservice has to solve is very hard (i.e. if there is a high number of zones and of sensors with different capabilities), then the webservice could start to use a lot of memory space, but also of CPU percentage work, to solve the problem.

## B.5 Source File Description

As we stated previously, there are three main components and the source code of them is grouped inside the folder `src` inside the installation CD. The directory `src` contains three subdirectories that reflect the system architecture.

- `Webservice` - which contains the Java source code of the developed webservice
- `CommanderInterface` - which contains the Java source code of the Interface for the commander
- `Battlefield 2 Mod` - which contains the Python source code of the BF2 mod

### B.5.1 Webservice source description

The Webservice is composed by one package "deploySensorsService" which contains a file "MyService.java" which implements the webservice, and a subpackage "deploySensorsService.solver" which contains all the classes that implement the solver of the problem to deploy sensors in the selected zones in an optimal way.

You will note that inside the folder "`src/webservice`" there are also other folders and installation files that need to be installed before modifying the webservice, since they are the platform that allows the webservice to work. Inside the folder "`src/ConfigWebService`" there are two files called "deploy.wsdd" and "undeploy.wsdd", the first is the most important since you will have to use it to deploy the webservice inside the Axis platform (as it is well explained

in the README file inside that folder), the second can be used in the case that you have to undeploy the webservice.

- Let's consider the package "deploySensorsService":

  **MyService.java** This class implements the webservice: the method "computeDeployment" performs the deployment of the sensors inside the zones, the other methods are used to return to the client the actual sensor deployment.

- Let's consider the subpackage "deploySensorsService.solver", where the class that actually solve the problem is "DeploySensors.java" which uses "ZoneDeploy.java" as an auxiliary class. The other classes are data structures and auxiliary methods used by these two main classes:

  **DeploySensors.java** This class performs the Sensor Assignment and then the Sensor Deployment of the sensors usign the class "ZoneDeploy". This reflects the actual model that divides the main problem into two subproblems: the Sensor Assignment and then the Sensor Deployment inside each zone of the sensors assigned to that zone.

  **ZoneDeploy.java** This class solve the Sensor Deployment problem for each zone considering only the sensors assigned to the zone.

  **Sensor.java** This is a data structure that represents the sensor and its properties.

  **CoveredArea.java** This is a data structure that represents the zone selected by the commander and the information that is required from it.

  **SubArea.java** This class represents a subzone created by division of a zone, this class is used in the algorithm that implements the Sensor Deployment problem solver.

  **MyList.java** This class implements a list using an hashtable and it is used as a utility class by the others.

  **PairInt.java** This class implements an object composed by a pair of integers

**Utilities.java** This class contains some utility function used by the classes "DeploySensors" and "ZoneDeploy".

### B.5.2 Commander Interface source description

The commander interface is composed by one package "deploySensorsClient" which contains a file "MyClient.java" and a subpackage "deploySensorsClient.structures". The first is the main class of the application and it implements the command-line interface, the second contains all the data structures used by the interface to perform its tasks (i.e. to send the request to the webservice).

- Let's consider the package "deploySensorsClient":

  **MyClient.java** This class implements the Commander's interface: it asks to the webservice for the solution of the problem whose parameters are set by the commander. This class uses the classes in "deploySensorClient.structures" to set the input parameters (sensors and zones) of the method "computeDeployment" of the webservice. It uses Axis libraries to communicate with the webservice.

- Let's consider the subpackage "deploySensorsClient.structures", where there are the data structures used by the commander interface to set the parameters of the problem. This classes are the same data structures used by the Webservice solver:

  **Sensor.java** This is a data structure that represents the sensor and its properties.

  **CoveredArea.java** This is a data structure that represents the zone selected by the commander and the information that is required from it.

  **SubArea.java** This class represents a subzone created by division of a zone.

  **MyList.java** This class implements a list using an hashtable and it is used as a utility class by the others.

### B.5.3 Battlefield 2 Mod source description

Battlefield 2 allows to develop your own plug-ins for the server, this plug-ins are called "mod" and they are written in Python and inserted into the folder "mods/[YourModName]". Each "mod" has to respect a proper structure, so it will have to include certain folders and files; in this structure you can insert your own Python code inside the folder "mods/[YourModName]/Python/game" that has to have a fixed structure too, but you can add also your own Python modules.

So the source of Battlefield 2 Mod is contained in the folder "src/Battlefield 2 Mod/game" inside the installation CD and it has a fixed structure. The real core of the Mod is implemented inside the file "scoringCommon.py" that is entirely written by me, Diego Pizzocaro. We used also other utility modules that are "Utils.py" and "Defines.py" which where taken from the Honors Project of Daniele Masato, whose name is PlanAndPlay[5].

- Let's consider the folder "game" it contains a folder "gamemodes" and other files of which the most important is "scoringCommon.py":

  **scoringCommon.py** This file is the core of the mod: It asks to the webservice for the current sensor deployment (that had been set before by the commander) and then it creates Sensitive Area inside the map simulating the behaviour of real sensors.

  **Utils.py** it contains some of the utility methods used inside the "mod" of BF2. This file is more or less the same of the one written by Daniele Masato, except that we deleted some functions that were useless for out own "mod".

  **Defines.py** it contains all the constants used inside the "mod" of BF2. This file is exactly the same of the one written by Daniele Masato except that we only use certain constants and not all of them.

[5]Indeed we took the same structure of the mod "PlanAndPlay" developed by Daniele Masato and, after having removed some part of the mod that we would not have used, we modified the file "scoringCommon.py".

## B.6 Compiling and Updating the system

Let's explain how to compile/update the different components of the system.

### B.6.1 Compiling the Webservice

To begin with, you could use an environment such as eclipse to edit the source code of the webservice. In this case you could create a new Java project, then import all the source files respecting the structure in packages (and so you have to create the packages inside eclipse), and finally you have to add to the project the needed libraries. For the last step you have to consider that to compile the project you have to add all the Jar files of Axis (contained in the folder where you installed Axis, inside the directory "axis-1_4/lib") an also the Jar file "choco-1.2.03".

Once you compiled the webservice you have to copy the compiled code inside Axis and then deploy the service. So the steps are:

1. Copy the folder "deploySensorsService" (you can leave into it the source code too) inside the folder where you installed Tomcat and in particular inside the directory "Tomcat 6.0/webapps/axis/WEB-INF/classes". You will have to delete the old folder "deploySensorsService" contained inside this directory and then you will have to paste the new one.

2. Start the Apache Tomcat service

3. Open a command prompt and browse to the folder of the project where you have also the files "deploy.wsdd" and "undeploy.wsdd". Now you have to undeploy the service with this command:

   ```
   java -cp %CLASSPATH% org.apache.axis.client.AdminClient undeploy.wsdd
   ```

   Where it is supposed that you set properly the variable "%CLASSPATH%" as explained in the README.TXT file inside the folder "src/WebService".

4. Always using the command prompt, you have now to deploy the service. And you can do this by writing the following command:

```
java -cp %CLASSPATH% org.apache.axis.client.AdminClient deploy.wsdd
```

5. Now restart the Apache Tomcat service and the new modified service should work.

### B.6.2 Compiling the Commander's Interface

Also in this case you could use Eclipse to edit the source code and compile it. Like previously explained you have to create a new project in Eclipse respecting the same package structure, and then to include the necessary libraries. In this case you have only to include the Jar file "choco-1.2.03". Once you compiled it you can also create a Jar File alway using Eclipse (or Netbeans if you prefer it).

### B.6.3 Updating the Battlefield 2 Mod

As you probably know, Python does not need to be compiled, it is usually an interpreted language and in this case the server will automatically execute the Python source code. So once you modified the Python source code contained in the folder "src/Battlefield 2 Mod/game" inside the installation CD, you just need to browse inside the directory where the Mod is actually installed (i.e. "Battlefield 2/mods/PlanAndPlay/python"), then delete the folder "game" and replace it with the new modified one.

## B.7 Known Bugs

Even if we tested the system quite a lot, it is likely that there are bugs in the system, which cannot be resolved because of the limited time assigned to this project. Here we document some known bugs in our system.

### B.7.1 Battlefield 2 Mod Bug

The BF2 server asks to the webservice for the stored deployment only when the first player connects to the server. In the meanwhile the commander could use the commander's interface to set another sensor deployment, but this deployment will not be used until all the players disconnect from the server. When the last remaining player disconnect from the server, it will reboot itself[6], so that all the sensors that were created inside the map are deleted. Now when a player connects again to the server, if it is the first who is going to connect, the server will ask again for the stored sensor deployment, and finally it will deploy the sensors inside the map.

The problem is located in the slice of time that the server spend to reboot itself. During this reboot time, a player can still connect to the server, but it will not have any deployment available, so in the map there will not be any sensor. In the future this bug could be resolved by not allowing players to connect to the server while it is rebooting.

### B.7.2 Webservice "Solver" Bug

The solver inside the webservice cannot always understand when a problem (whose parameters are set by the commander) has no solution. When the problem is quite "easy" it manages to answer that there is no solution, but when there are too many variables it could go on forever trying to find a solution. In the future this could be resolved by using a time limit, so that after this fixed time the solver will stop to look for a solution and will answer that there is no available solution.

[6]In this case with the term "reboot" we mean the operations that the server carries on to reload all the Python modules.

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[Translation:]

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